AF INSTITUTE OF TECHNOLOGY

AN ASSESSMENT OF FORECASTING METHODS: COOPERATIVE LOGISTICS SUPPLY SUPPORT ARRANGEMENT (CLSSA) INVESTMENT ITEMS

THESIS

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AFIT/GLM/LAL/94S-20

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THESIS

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ABSTRACT

The United States (US) promotes collective security in the Free World via the Foreign Military Sales (FMS) program. FMS customers prefer to acquire weapon system logistic support through FMS rather than by direct commercial vendor support. Ninety-seven percent of the follow-on logistics requirements are submitted via a special program called Cooperative Logistics Supply Support Arrangement (CLSSA). CLSSA, while sound in theory, has been a poor performer. The USAF must modify the CLSSA program or risk losing future FMS sales to competing nations. Modifying CLSSA to utilize an automated forecasting process versus the current manual process will greatly improve customer service. Efficient and timely logistic support is a key decision factor as friendly nations evaluate the source of their next major weapon systems acquisition. The US as a whole will gain from the USAF's new approach to CLSSA through the political, military and economic benefits that result from increased FMS demand for US weapon systems.

AN ASSESSMENT OF FORECASTING METHODS: COOPERATIVE LOGISTICS SUPPLY SUPPORT ARRANGEMENT (CLSSA) INVESTMENT ITEMS

I. Introduction

General Issue

The United States (US) promotes the principle of collective security among the nations of the Free World. The US Joint Chiefs of Staff state, "Collective security is and must continue to be a vital objective of political, economic, social and military interaction and cooperation between the US and its friends and allies" (19:35). One method the US uses to promote collective security is by offering to sell its defense systems to other nations via the Foreign Military Sales (FMS) program. Government to government contracts called Letters of Offer and Acceptance, commonly referred to as cases, are the formal basis for all FMS sales.

The total cumulative sales of the Department of Defense (DOD) FMS program, as of August 1993, were valued at $220.8 billion. Air Force Security Assistance Center (AFSAC) is responsible for the administration of $ 98.1 billion, 44.4 percent of this DOD FMS total (22:1). AFSAC provides FMS logistic support to eligible countries and international organizations through initial support packages and through follow-on support cases. An initial weapon system sale consists of the weapon systems (C-130, F-16, F-15) and the logistic support necessary (spares, support equipment, technical

assistance, training, publications) to establish an in-country operational capability. The initial sales case typically provides for logistics support just for the initial operating phase (normally two years). Follow-on support cases, as the name implies, provide the subsequent material and services necessary to continue operating and maintaining the system and equipment through its remaining service life.

Customer countries overwhelmingly prefer to acquire defense systems' follow-on logistic support through additional FMS cases rather than direct commercial support (19:337). At AFSAC, ninety-seven percent of these follow-on requisitions are submitted via a special logistics support program called Cooperative Logistics Supply Support Arrangement (CLSSA). The CLSSA program is designed to enhance timely follow-on spares and repair support by providing a mechanism for the FMS customers to participate in the USAF supply system. To participate in CLSSA, the FMS customer must project anticipated future requirements and provide an initial deposit equal to 5/17 or 29.4 percent of the materiel value of their requirements. The USAF then places the materiel on-order so that when the FMS customer actually needs the materiel, the materiel is either already on-hand ready for shipment or on-order with most of the procurement lead time having already transpired.

Two types of FMS cases form the basis of the CLSSA program: the Foreign Military Sales Order I (FMSO I) and the Foreign Military Sales Order II (FMSO II). Each FMS customer has a unique FMSO I and FMSO II case combination. Each respective customer identifies its requirements by National Stock Number (NSN) and quantity on the FMSO I case. These requirements are used to calculate the initial deposit to be collected from each customer. The requirements for each NSN and quantity are consolidated by the Security Assistance Management Information System (SAMIS) and then forwarded to the source of supply for procurement action. The FMSO II case is used to withdraw items from the DOD supply system at full material value. Basically, the FMSO I orders materiel

into the DOD inventory in anticipation of subsequent FMS demands, and the FMSO II pulls the materiel from the DOD inventory and provides funds for the procurement of a replacement item. The AFSAC managed FMSO I cases are collectively valued at $1,086,275,576, as of 7 March 1994, and the FMSO II cases had an annual requisition value of $715,289,936. Cumulatively, the CLSSA program has an impact on the DOD supply system of $1.8 billion (2:1).

The general issue of this thesis concerns the FMSO I portion of the CLSSA program. The FMSO I does not operate in an efficient manner for investment items. Thirty-six percent of all investment items on the FMSO I case have had no demands in the past four years and fourteen percent of the items added to the FMSO I in the past four years also have had no demands (2:1). Over the past 10 years, only about forty-five percent of the investment item requisitions submitted received the benefits of preferential supply treatment offered by CLSSA (see Figure 1) (2:1).

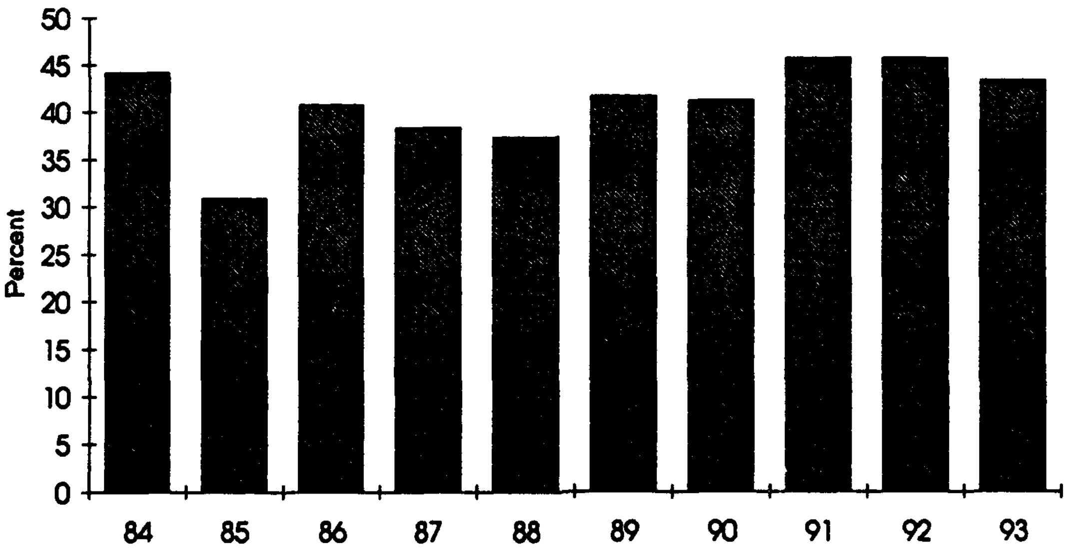

Figure 1. Yearly Percentage of Programmed Requisitions (2:1)

This poor performance is a clear indicator that the USAF needs to modify the CLSSA program to ensure that it operates efficiently and provides quality, timely spares support in response to the foreign customers' investment. If the USAF cannot provide timely logistic support for its weapon systems, the use of FMS and its associated reliance on the personnel and material resources of friendly governments for augmented support in conflicts will diminish. Loss of FMS sales would also mean a loss in political, military, and economic benefits for the US as a whole. To continue to share these support costs with the allies and to maintain the US defense industrial base, the USAF must continue to provide efficient, quality customer logistic support.

Background

Currently, there are fifty CLSSA participants out of the seventy-six countries and two international organizations that purchase follow-on logistic support from the US (2:1). The participants are financially liable for the total amount of their FMSO I individual cases. However, they are only required to deposit five-seventeenths of this amount. It is the participant's five-seventeenths investment that gives the DOD the authority to buy and store items in anticipation of participant's requisitions. The five-seventeenths amount equates to the portion of items in the FMSO I case that is either on order or on the shelf. As of 7 March 1994, the five-seventeenths portion of the collective FMSO I investment ($1,086,275,576) was $319,492,816 (2:1). Payment of the twelve-seventeenths portion of the case is not normally collected. However, the participant is financially liable for the material if the stocklevel case is reduced or the case is terminated (8:2-4).

The CLSSA program uses the FMSO I case to provide demand projections and funding for the purchase of follow-on spare and repair support. The FMSO II case is an

annual requisition case that permits the CLSSA participant to requisition spares and repair parts from the USAF as in-country spares are consumed. It is defined in terms of dollar value and does not identify either items or quantities (8:9-1). The FMSO I identifies the participant's spares requirements, financial liability, and financial investment in the USAF and Defense Logistic Agency (DLA) supply systems. The spares requirements are identified by NSN and quantity for reparable items (investment item) on a FMSO I requirements listing. The NSN and quantity listed on the FMSO I requirements listing is referred to as the Stocklevel Quantity (SLQ). The spares requirements for expendable (consumable) items are managed by dollar value only. The dollar value of expendable items is based on actual programmed requisitions received over the last two years adjusted to an average seventeen month demand (8:3-1 to 3-4). The CLSSA concept provides the customer and the USAF with numerous economies of scale resulting in reduced reprocurement, inventory, inventory holding, and obsolescence costs. However, most customers feel that the most beneficial portion of the program is the reduction in the supply lead times for spares and repair parts.

In order to receive the full benefits of the CLSSA program, the customer must ensure that his FMSO I case contains items that are actively used by his country. Preferential supply treatment offered by CLSSA is referred to as 'programmed' support. Through the proper management of the FMSO I case, the customer can ensure that all his requirements receive programmed support. The benefit of a programmed requisition versus a nonprogrammed requisition is in the amount of stock on the shelf that can be shipped to fill the requisition. Programmed requisitions are eligible to be filled from stock down to the zero level. Nonprogrammed requisitions are eligible to be filled from stock only if the on hand assets are above the item manager's control level. Thus, if the item manager's asset position was at the control level a programmed requisition would be immediately filled to the zero level. In this same situation, a nonprogrammed requisition

would be lead time away, resulting in support delay, and most likely an increased unit price (8:9-1 to 9-5).

There are two criteria that must be met for the requisition to receive programmed support. The first criterion is the FMSO II requisition itself. The requisition is eligible to receive programmed support, if card column 44 of the requisition contains an "R" or a blank. If card column 44 contains an "N", the requisition is treated as nonprogrammed regardless of criterion two.

Criterion two is a bit more complicated and relates to the FMSO I case. For an investment item to receive programmed support, the NSN must be listed on the FMSO I, and the quantity of the requisition must be less than or equal to the remaining eligible to be programmed quantity (EPQ). The EPQ is the portion of the total SLQ that has not been requisitioned within the actual procurement lead time of the item (8:9-1 to 9-4). For example, if the SLQ is 20 and the EPQ of a particular NSN is 20, a requisition for 20 would receive programmed support. However, if the requisition was submitted for 30 the whole requisition would be coded as nonprogrammed. Assuming the SLQ and EPQ are 20 as before, if a requisition for 20 were submitted today, the total quantity of the requisition would receive programmed support and the EPQ would be reduced to zero for the length of the procurement lead time. After the procurement lead time had expired, the EPQ would be increased back to 20 and another requisition could be submitted and receive programmed support. Any requisition submitted while the EPQ was zero would be nonprogrammed. For expendable items, all requisitions are coded as programmed or nonprogrammed based on criterion one. The only exception to this rule is during the first year of the CLSSA program or a Major Add to the CLSSA program, resulting from the addition of a new weapon system (8:9-5).

FMSO I Development and Modification

The FMSO I can be developed and modified in three ways - Initial Program, Major Add Programs, and File Maintenance:

a. The Initial Program is used when a participant first joins the CLSSA program. Before participation in the CLSSA program the participant provides the USAF with the operational and maintenance data for the weapon system it wishes to support. Normally, the USAF System Manager (SM) uses this information to develop a recommendation of items and quantities required to support the system. The listing of recommended items can also be obtained from previous FMS demand data, contractor data, or other country data sources. SAMIS processes the SM recommendation based on FMSO I Eligibility and Exclusion Criterion. The results of this processing are a listing of items eligible for the FMSO I (the CLSSA Recommendation Listing) and a listing of the items ineligible for the FMSO I (the CLSSA Ineligible Item Listing). The items listed on the CLSSA Ineligible Item Listing may be procured using other FMS cases specifically designed for the procurement of the non-CLSSA items. For example, ammunition type items in Federal Supply Group 13, although required for weapon system support, are ineligible for the CLSSA program. However, these ammunition items can be ordered on an unique FMS case with an "A" case designator (8:2-2).

The CLSSA Recommendation Listing contains the NSN, quantity, and dollar value for investment items along with a recommended dollar value only for expense items. This listing is then forwarded to the participant for modification or approval. The participant makes any desired changes and returns the listing to AFSAC. After the modifications are incorporated, the approved items and values (CLSSA Stocklevel Requirements Listing) are used to generate the FMSO I case (8:2-1 to 3-4).

b. A Major Add is used for the addition of a new weapon system or a large

number of items for a current system to the FMSO I case. Normally, the USAF SM prepares a recommendation of the items to be added. This recommendation is then processed by SAMIS to generate the CLSSA Recommendation Listing and the CLSSA Ineligible Item Listing. After the country reviews, approves, or modifies the CLSSA Recommendation Listing, the AFSAC prepares an amendment to the original FMSO I case (8:6-1 to 6-5).

c. File Maintenance is the adjustment of FMSO I stocklevel items and their quantities as the participant's requirement changes. File maintenance can be done on a daily basis by the use of file maintenance transactions. File maintenance transactions can decrease or increase the SLQ by NSN, as well as add or delete a NSN from the CLSSA Stocklevel Requirements Listing. The participant is responsible for preparing the file maintenance transactions and forwarding them to the AFSAC case manager or inputting them directly into SAMIS (8:4-1 to 4-5).

Renegotiation (Financial Update)

Since the FMSO I is an on-going case, the value can vary based on changes in the participant's requirements. AFSAC renegotiates the FMSO I case every six months to financially update the FMSO I case value. AFSAC uses the participant's two year demand history and the existing stocklevel requirements to produce a CLSSA Stocklevel Renegotiation List. The CLSSA Stocklevel Renegotiation List shows:

1. Catalog Management Data including noun, source of supply, unit of issue, procurement lead time, Expendability, Recoverability, Repairability, Category code, and Interchangeability and Substitution Group for each NSN (8:7-1).

2. The current SLQ for each investment item in NSN sequence (8:7-1).

3. A two year demand history by program/nonprogram code (8:7-1).

4. A requirements projection based on the demand history for each NSN (8:7-1).

The renegotiation list was intended to be used by the participants to evaluate their current investment items' SLQ and make adjustments based on current and projected operational requirements (8:7-2 to 7-3). However, for many CLSSA participants, renegotiation is a difficult task. Many participants do not have established procedures to calculate item by item demand requirements. The task of demand calculation is frequently passed to junior officers who do not have the experience or tools necessary to make good predictions. This results in items and quantities on the CLSSA that did not receive the level of customer country management necessary to ensure that the country's CLSSA reflects their actual needs.

A methodology is required that will match the spare items and quantities purchased under CLSSA to the actual foreign customers' demands. At the present, over 36% of the investment items bought under the current USAF CLSSA procedures have not been ordered by any customer over the past four years (1:1). This means that the foreign customers' investment purchased items that are no longer required or are very low demand items (items which were demanded less than once every four or more years). The funds used for these purchases could have been used more effectively, if a method existed, to accurately predict the items actually demanded. The estimated amount of funds obligated to these "no demand" items is around $319M out of a $1B program. This amount has been growing over the last few years at a 7 to 10 percent rate (1:1). FMS customers are rightly concerned because: 1) the items on the shelf are tying up funds that could be used for the procurement of high turnover items, and 2) the price of the items is constantly increasing (through inflation and storage charges).

The impact on problem two has been greatly increased by the USAF implementation of Defense Management Review Decision (DMRD) 904 in October 1992. DMRD 904 directed the stock funding of reparables (7:6-7). Stock funding had a direct

impact on CLSSA investment items because almost all investment items are reparables. Before reparables could be converted to the stock fund concept, the reparable inventory had to be capitalized. This capitalization action increased the price of CLSSA investment items in inventory between 5 and 37 percent (2:1). The percentage of increase was based on the date of the last procurement (acquisition cost). If the item had not been bought for years, as in the case of some F-111 and F-5 aircraft components, the price increased close to 37 percent (2:2).

Prior to the implementation of DMRD 904 the stock list price of an item was only updated (increased or decreased) when a reprocurement action was taken. This meant that once the CLSSA customer added an item to the FMSO I case, it could remain on the case indefinitely without experiencing a price increase, even if there was no usage for the item. However, under DMRD 904, the price of the item will be adjusted (increased or decreased, but mostly increased) each year. Therefore, if the customer maintains an inactive item on the FMSO I case, and the price of the item increases each year, the customer will be assessed a higher price to keep the item on the FMSO I case (the 5/17 amount required to be on deposit will increase). In addition, the customer will be assessed a higher price (the current stock list price) when the customer removes the item from the case with a file maintenance transaction (7:6-7). Thus implementation of DMRD 904 imposed a twofold penalty on the CLSSA customers who do not actively manage the NSNs on their FMSO I case.

Current Method

The current USAF CLSSA process relies on each customer country to predict the investment items by NSN and quantity to which each customer's CLSSA investment funds should be applied. AFSAC intends to shift the CLSSA program from a manual customer

country item/quantity management basis to an automated item/quantity management basis where calculations are based on historical country demands against the USAF supply system. A method needs to be identified that accurately predicts CLSSA investment items on a quarterly basis from historical demand data. This method must also be capable of quickly adjusting for increasing or decreasing demand trends within the procurement lead time or the repair turn around time of the item. Accurate forecasting of future CLSSA reparable demands is vital to the successful operation of the new USAF CLSSA program.

Specific Problem

The purpose of this research was to examine the ability of four time-series based forecasting methods to improve the quality of the FMSO I stocklevel. For this thesis, a quality stocklevel is defined as one that identically matches the customer's actual requirements, in terms of having the correct NSN and quantity available, when a customer demand is received. The quality of the forecasted stocklevel was determined by measuring the amount of error between the stocklevel quantity forecasted by the models and the actual CLSSA quantity demanded. Based upon experience with the CLSSA program and the information obtained in the literature review, three traditional forecasting methods were selected that appeared to offer the greatest potential for producing accurate CLSSA forecasts. The three traditional forecasting methods are double exponential smoothing, adaptive response, and classical decomposition. The results from these methods were compared with a unique time-series method developed by the AFSAC, called the "retention formula." The product of this research was a rank order listing of the tested methods based upon the accuracy of each method to predict the quantity of future CLSSA demands. This research focuses on identifying whether an automated method of

predicting investment item demands will outperform the current manual method of predicting future CLSSA requirements.

Investigative Questions

1. How accurate are the forecasting methods in predicting future CLSSA demands?
2. To what extent, if any, will trends, cycles, and seasonality have on the accuracy of the forecast?
3. What degree of improvement, if any, is achieved by each of the four forecasting methods over the current method?
4. What degree of improvement, if any, is achieved by the three traditional forecasting methods over the proposed AFSAC forecasting method?
5. In general, will forecasting based on historical demands result in higher or lower quantities of CLSSA reparable (investment) requirements compared to the current method?
6. In general, will the amount of investment funds need to increase to support the quarterly CLSSA reparable requirements predicted by the forecasting method?

Scope and Limitations

This research, sponsored by the AFSAC, concentrates on the USAF high cost, reparable items which the CLSSA refers to as investment items. The research task examines several potential methods to calculate the items and quantities to be purchased with the FMS customer investment in the CLSSA and to determine which method provides the greatest benefit to the CLSSA participants. This research does not:

1) address the overall performance of the CLSSA program

2) evaluate the benefits of using a stock fund concept for reparable items

3) discuss the accuracy of the methods used to develop the USAF's initial or Major Add recommendations

4) measure the performance of the DOD supply system after the quarterly requirements are forwarded

5) assess the appropriateness of selecting 5/17 of the FMSO I value as the country's investment in the CLSSA

6) examine the validity of the periodic repricing of investment items already in the inventory to adjust for inflation

7) analyze the forecasting algorithms coded in the forecasting software package used in this research.

II. Literature Review

Introduction

This literature review examines aspects of inventory management relevant to the USAF investment/reparable item portion of the Cooperative Logistics Supply Support Arrangement (CLSSA) program. The first part addresses the legislative environment that has dictated a change in the method of managing reparables. The next section focuses on the need to select an appropriate forecasting method to manage CLSSA reparable items. Finally, the review examines the forecasting dilemma and the major traditional forecasting methods which are potentially applicable to the research problem.

Background

The CLSSA is a Foreign Military Sales (FMS) supply support agreement that permits foreign governments to invest funds in the Department of Defense (DOD) supply system. These foreign investment funds are used by the USAF to augment the DOD's stocklevels. CLSSA customers benefit from participation by having their requisitions filled directly from DOD inventories. The Defense Institute of Security Assistance Management defines CLSSA as,

> Military logistics support arrangements designed to provide responsive and continuous supply support at the depot level for US made military materiel possessed by foreign countries and international organizations. The CLSSA is normally the most effective means for providing common repair parts and secondary item support for equipment of US origin which is in allied and friendly country inventories (19:562).

For the CLSSA to operate efficiently, the investment funds must be used to purchase, in advance, the range and depth of items that will be ordered in the future by CLSSA participants. At present, over 36 percent of the investment items bought under the USAF CLSSA program have not been ordered by any FMS customer over the past four years; therefore, an improvement in forecasting methods is warranted (1:1).

Research Purpose

The purpose of this research was: 1) to compare the accuracy of four forecasting methods in predicting CLSSA quarterly investment item demands, 2) to compare the performance of the most accurate to the current CLSSA program, and 3) to identify the most accurate of these four forecasting methods for possible use by the new USAF CLSSA program.

Legislative Environment

Two Defense Management Review Decisions (DMRDs) had a drastic impact on the CLSSA program. DMRD 971 set guidelines for a new revolving fund, the Defense Business Operations Fund (DBOF). The DBOF directed the development of a cost per output system for DOD implementation applicable to every management level. The DBOF permits identical measurements in like functions. The DBOF measures are responsible for the creation of the Cost of Operation Division (COD) portion of the reparable stock fund (6:1-8). DMRD 904 directed the stock funding of reparables (7:6-7). Before reparables could be converted to the stock fund concept, the reparable inventory had to be capitalized. This capitalization action increased the inventory cost of reparable items in the CLSSA program between 5 and 37 percent (2:1). The percentage of increase

was based on the date of the last procurement (acquisition cost). If the item had not been bought for years, as in the case of the F-111 and F-5 aircraft, the price increased close to 37 percent (2:2). Below is an excerpt from the Stock Fund Operations DOD Directive on the capitalization process:

> The acquisition cost is used to establish an item's standard price. For items without a procurement history, an acquisition cost is estimated based upon current manufacturer's price listings or market quotations. The acquisition cost of an item procured by a multi-year contract may include up front costs such as set up cost that will not be incurred in future years. (3:4-1)

Need for Forecasting

Today's managers need to understand how the stock fund process works and how it impacts their programs. In an environment where limited funding resources must be maximized to get the best return on investment, efficient management of operations and maintenance dollars under the stock fund concept is critical. As the military focuses on the cost of doing business, stock funds will take on increased importance (4:1-2). It may not be long before almost every item issued through the CLSSA program will be stock funded. The USAF CLSSA program must adjust its management philosophy to survive.

Inventory control is a key aspect of stock fund management. Accurate, reliable requirements determination processes are required to ensure the future readiness demands are realistic (9:1-2). Proper development and application of trend analysis provides managers capability to accurately project future levels. By comparing past and present performance with known future projects, managers will possess the required information to make accurate inventory decisions. Forecasting sales becomes a tool for sound financial management (5:29-165).

The CLSSA program was structured to allow the FMS customers to adjust the

National Stock Number and quantity of investment items on a daily basis as their demand for the item changed (8:4-1 to 5-3). It was envisioned that customers would be in the best position to know their own future requirements. This philosophy, however, has resulted in an average customer error of 36 percent (1:1). Customer error is defined as adding the NSN to the FMSO I case and then not placing a requisition for the item. In addition, 14 percent of the items added by the FMS customer in the last four years have not been requisitioned. Overall only about 45 percent of investment item requisitions are coded programmed (24:1).

The impact of having incorrect items on the CLSSA stocklevel case prior to the implementation of the stock fund was that, overall, 55 percent of the country's investment was incorrectly allocated based on their demand patterns (1:1). Since the cost of these items was recorded at historical procurement prices, the amount of error (incorrect investment) remained the constant. However, under the stock fund capitalization concept, the cost of leaving incorrect items on the CLSSA stocklevel case increases each year. The use of accurate forecasting and Air Force Stock Fund reports will help management overcome the pitfall of allowing inventory to grow unnecessarily by not knowing what the customer needs.

USAF Reparable Forecasting Methods

Since CLSSA forecasts interface with the USAF D041 reparable management system on a quarterly basis, it is beneficial to understand the D041 forecasting model. The D041 system uses a single moving average forecasting model which uses the most recent eight quarters of data as its basic forecasting method. The basic model is supplemented with a weighted single moving average forecasting model to compute the overall demand rate. Consequently, it is important to understand that when the quarterly programs follow

a decreasing trend, the computed weighted single moving average demand rate will be less responsive to the trends in the quarterly rates than will the single moving average. Also, if the quarterly program's demand rate follows an increasing trend, the computed weighted demand rate will be smaller than the single moving average of the rates. Where the program is approximately constant over time, the weighted demand rate is essentially computed using the single moving average (10: 28-34,41). The D041 model emphasizes that forecasters need to pay attention to changes in the direction of the variables, as well as the average value of the variables (11:162-163).

Forecasting Dilemma

An anonymous author correctly summarized the forecasting dilemma by the statement "The future isn't what it used to be" (12:49). Forecasts are intended to describe what will happen in the future given a set of circumstances (13:4). Difficulties arise when the set of circumstances is dynamic and fluctuates over time (16:445). Most forecasts of demand are reliable for a short time period into the future; however, the validity of the forecast can drastically deteriorate within a very short period depending upon the characteristics of the forecasting environment (17:60). Effective forecasting must match the characteristics of the situation or process at hand with the characteristics of a forecasting methodology (13:33). Demand data consist of four basic patterns which must be analyzed separately to assure forecast accuracy (16:445). The four basic data patterns are irregular, seasonal, cyclical and trend. The irregular pattern contains apparent random and unexplainable changes over time with no systematic pattern of increasing or decreasing. This pattern is often referred to as noise. The seasonal pattern displays fluctuations according to some time related factor within a year (13:20). A trend pattern is a general increase or decrease in the value of the forecasted variable over time. The

cyclical pattern is similar to the seasonal pattern, but the patterns recur at intervals longer than one year. The cyclical pattern is difficult to detect since it does not repeat frequently. This pattern consists of a general tendency of continued increase or decrease over a relatively long period of time (13:21).

Accurate forecasting requires a model that matches the characteristics of the process under consideration. The four primary model categories are briefly described below (13:25-26):

Time-series - This model assumes that a historical pattern exists and that this pattern will recur over time. Knowledge of the historical pattern permits prediction of a future period.

Explanatory - This model assumes that the value of the dependent variable is a function of several independent variables rather than as a function of time. Computation methods involve use of multiple regression analysis. If this model is to be applied for future periods, accurate forecasts of each contributing variable must be calculated before the variable of interest can be calculated.

Statistical - This model uses statistical analysis to identify variable patterns and to determine the reliability of forecasts. Although these models are more precise than others, they are not used extensively due to their complexity and difficulty in practically applying the results.

Nonstatistical - This model is based upon intuitive inputs rather than quantitative input and analysis. These are the "common sense" models used to estimate future values.

Forecasting Methodologies

The following traditional methodologies were identified during the literature review as possible candidates for use in CLSSA investment item forecasting. Three

traditional forecasting methods will be selected based on their ability to predict the future using a historical time series.

Naive I - This simple approach just uses the most recently observed value as the forecast value. This method gives no weight to other past observations (13:37; 14:21; 15:570; 16:499).

Naive II - This method is the same as Naive I except the current observation is deseasonalized to a generic value. The observed value is then reseasonalized using the seasonal factors applicable to the particular forecast period. Both of the naive methods are useful to establish a baseline to compare competing alternate models to determine whether the additional accuracy of the more sophisticated methods is worth the additional time and cost (13:37; 14:21; 15:571; 16:449).

Single Moving Average - This method seeks to minimize the random fluctuations of the naive methods. An average value is computed by summing the observed values of several periods and then dividing the summed value by the number of periods. Each period is given equal weight in the forecast. The "moving" element is derived from dropping the observed value from the oldest period and replacing it with the observed value from the most recent period. Significant drawbacks of this method include negating seasonal factors through the averaging process and a slow response to changes. The greater the number of periods included in the average, the greater the "smoothing" effect will be on the fluctuations in the historical observed values. Because of these limitations, the moving average should only be used for forecasting variables that exhibit a flat data pattern with little randomness (13:55-61; 14:44-49; 15:45-48; 16:454-455).

Double Moving Averages - This model first computes a single moving average value using observed data as described above. A second average is then computed. This second average is computed using historical single moving average data from past periods. The difference in value between the single moving average value and the double moving

average is added back to the single moving average value to arrive at a forecast value. The drawback to double moving averages is that twice the amount of data points are required as the single moving average method. The strength is that they produce much more accurate forecasts when the data displays a increasing or decreasing trend (13:67-70; 14:48-54; 15:56-60; 16:454-455).

Single Exponential Smoothing - This method is similar in concept to the moving average except equal weight is not given to each observed value. Greater weight is given to the most recently observed values by applying exponential weights. The amount of weight placed on each observed value decreases as the historical data becomes older. An alpha term (between 0 and 1) controls the degree of smoothing in the forecast. Higher values of alpha provide little smoothing and result in a greater response to recent changes in observations. Lower values of alpha provide greater smoothing of the fluctuations in the data (13:61-65; 14:58-66; 15:48-53; 16:455-458).

Double Exponential Smoothing - This method in concept is similar to the double moving average method. In this method, a single exponential smoothed value is calculated. Next, a double exponential smoothed value is calculated using the single exponential smoothed values as input. The difference between these two calculations is added back to the single smoothed value for a forecast value. Double exponential smoothing produces more accurate results than single exponential smoothing when trend patterns exist in the data. Research has found that the double exponential smoothing method always produces more accurate results than the double moving average method (13:70-73; 14:79-80; 15:55-60).

Winters' Three Parameter Linear and Seasonal Exponential Smoothing - This method is similar to double exponential smoothing except it has the capability to incorporate both a trend adjustment and a seasonal adjustment. This method involves three equations. Each of the equations smoothes one of three patterns (randomness, trend

and seasonal components) in the data. The drawback to this method is that various smoothing values must be selected on a trial and error basis to identify the combination that produces the smallest mean square of error (13:73-78; 14:98-105; 15:72-73; 16:458).

Harmonic Smoothing - This method is specifically oriented towards calculating seasonality in time series data. The method uses Fourier analysis to transform the data to sine and cosine terms for the calculations. In situations where data is limited, this method tends to predict seasonal turning points better than exponential smoothing; however, when adequate data is available, decomposition and autoregressive moving averages perform better (14:184).

Adaptive Response - This method uses weighted historical data to forecast future values. The value of the weight applied to each historical data value is recalculated for each new forecast period. The amount of adjustment to the weights is based upon the amount of error that occurred between the previous period's forecast value and actual value. This is a dynamic method where the weights will be continuously adjusted. The adaptive capability of this method permits it to effectively respond to changes in the patterns of the underlying data. This method usually produces more accurate results than the moving average and exponential smoothing methods; especially when the historical data contains a complicated underlying pattern (13:82-96; 14:266-274; 15:286-299).

Simple Regression - This is an explanatory method rather than a time series method. This method assumes a underlying linear pattern in the historical data. Unlike time series methods, this method makes predictions based upon a causal relationship between a readily measured independent variable and the unknown value of the dependent variable. A mathematical linear equation calculates a line which predicts the value of dependent variable given the value of the dependent variable as input. Statistical analysis of the equation permits identification of confidence intervals, coefficient of correlation and coefficient of determination. These statistical calculations reveal the usefulness of the

linear model in predicting values of the dependent variable (10:455-522; 13:101-121; 14:120-127; 15:146-165; 16:464-465).

Multiple Regression - This method is essentially the same as simple regression and correlation except multiple independent variables are included in the model. The addition of multiple independent variables typically permits greater accuracy in predicting the dependent variable's value. The goal of multiple regression is to identify and include the key variables that influence the value of the dependent variable. Drawbacks of multiple regression include high costs to gather data continually on the independent variable and difficulties in determining when the causal relationship between the dependent and independent variable changes. As a result, multiple regression is generally used to forecast aggregate variables such as overall level of economic activity rather than for individual variables such as demands for specific products (10:522-589; 13:146-168; 14:363-382; 15:180-220).

Classical Decomposition - Most time series methods attempt to produce forecasts by accounting for the cumulative impacts of trend factors, cyclical factors and seasonal factors. The decomposition method separates the overall data pattern into individual subparts of trend, cycle and seasonal elements. This method can be used to explain fluctuations in data values and permits predictions to be tailored to reflect trend, cycle and seasonal changes (13:123-145; 14:198-209; 15:88-138).

Univariate Autoregressive Moving Average (ARMA) - This category of methods uses one independent variable (univariate) to predict the dependent variable. Autocorrelation calculations determine patterns within the data. Autocorrelation is the amount of correlation which exists between values of the same variable measured at incremental time intervals. For example, the correlation between seasonal temperature measured at 12 month intervals constitutes an autocorrelation calculation. The term "autoregressive" identifies the similarity to the single and multiple regression methods.

Here, the independent variable values are simply the values of a single variable measured at different time lag periods from the current period. The term "moving average" refers to using the average difference between predicted and actual values from past periods in making the current forecast. This category of methods has proven to be very accurate but these methods are complex and expensive in terms of computer time to operate. As a result, there has not been a large amount of practical application (13:171-196; 14:383-387; 15:328-361).

Multivariate Autoregressive Moving Average - This category of methods utilizes the same processes as ARMA methods but permits inclusion of multiple variables in predicting the value of the dependent variable. Inputs from the additional variables make the forecasts more accurate but also make these methods even more complex, difficult to use and costly to develop than univariate ARMA methods (13:197-198; 14:387-392; 15:376-428).

Selected Forecasting Methods

The three traditional forecasting methods of double exponential smoothing, classical decomposition, and adaptive filtering were selected based on the literature review's indication that these methods were the most accurate using the hypothesized CLSSA underlying time series data patterns. The double exponential smoothing method was selected as the time series based method that provided the most accurate results under the assumption that trends, cycles, and seasonal impact did not exist in the data. The two additional models, the adaptive filtering and the classical decomposition models, were selected based on their ability to enhance the time-series forecast using underlying trends, cycles, and seasonality.

Summary

The three traditional forecasting methods of double exponential smoothing, classical decomposition, and adaptive response were selected for testing based on the literature review's indication that these methods would be the most accurate analytical forecasting methods that correspond to the presumptive patterns within the data. The double exponential smoothing method was selected as the time series based method that provided the most accurate results under the assumption that trends, cycles, and seasonal impact did not exist in the data. The two additional models, the adaptive response and the classical decomposition models were selected based on their ability to enhance the time-series forecast using underlying trends, cycles, and seasonality.

This chapter presented background information on the CLSSA program and some of the reasons why a new CLSSA forecasting method is required. The purpose of forecasting is to isolate the basic pattern in the historical data and then use this knowledge as a basis to predict future values. The accuracy of the forecast depends upon selection of the correct category of model that reflects the characteristics of the particular forecasting situation. A number of forecasting methodologies have been developed in response to the various types of data patterns. This review briefly described nine major forecasting methods which could be applied in CLSSA forecasting research.

Chapter III describes the methods to be employed to test the performance of four models in predicting CLSSA investment item demands. The models tested were double exponential smoothing, adaptive response, and classical decomposition. A discussion of the test results is presented in Chapter IV.

III. Methodology

Chapter Overview

This chapter describes the population of interest and the research design utilized to control and select the sample data used in this study. The forecasting methodologies applied are then briefly described followed by an outline of the forecasting process and a description of the forecasting software. Next, performance measures, cost measures and validity issues are discussed. Finally, the limitations of the research methods are presented.

Controlling Population of Interest

This research focused on examining the demand characteristics of Cooperative Logistics Supply Support Arrangement (CLSSA) investment items. The population of interest is all USAF CLSSA investment item records. The CLSSA program began in mid-1962 and utilized the HO51 computer system. In 1983, the International Logistics Center converted to a new computer system named the Security Assistance Management Information System (SAMIS). Although SAMIS contains all USAF Foreign Military Sales (FMS) requisitions, for the purposes of this research, only records of CLSSA investment item demands were of interest. For analysis purposes, the population of CLSSA records was further reduced to a ten year sample period. The range of sample data covers the period from 1 January 1984 to 31 December 1993. This continuum of data was segmented into chronological quarters to coincide with the USAF quarterly forecasting method. This ten year range produced 40 quarters of data which is considered a large sample for statistical analysis. This range of data includes the implementation of

the Defense Management Review Decision (DMRD) 904 on 30 September 1992, Operation Desert Shield from 2 August 1990 through 17 January 1991, and Desert Storm from 17 January 1991 through 28 February 1991 as possible distortions to the data patterns. However, it was felt that the chosen forecasting model must be able to react to demand fluctuations as a result of the legislative or political situation.

Sample Selection

The population of CLSSA investment items consists of 10,969 National Stock Numbers (NSNs). It was hypothesized that dividing the sample into three categories based upon number of demands would provide the opportunity to measure each model's performance to forecast based on volume of historical demands. The three demand categories are referred to as low, medium and high. To improve the validity of the results, a statistically large number of NSNs was required in each category. Statistically, a sample size of at least 30 is considered large (18:35). For this reason, at least 30 NSNs were desired in each category. Additionally, the population was hypothesized to display a normal distribution, meaning that approximately one third of the total number of NSNs would fall into one of the low, medium or high demand categories. Based on the above information, a sample size of 100 NSNs with demand data was desired. However, the literature review indicated that approximately 36 percent of the NSNs in the population would not have any demand data (1:1). Therefore, in order to obtain a usable sample size of 100 NSNs, it was necessary to select 136 NSNs from the population.

From the population, 136 NSNs were randomly selected to be used as sample data for comparing forecasting methodologies. A statistics software program, *Statistix* Version 4.0, was used to generate 136 random numbers between the values of zero and one (27). Each random number was multiplied by 10,969, truncated to the closest whole number

and then one was added to its value. For example, if the random number generated was .9999, .9999 times 10,696 equals 10,967.9. The result is then rounded to the nearest whole number or in this case 10,968. If a value of one were not added, the chance to select NSN 10,969 would not exist. A second reason for adding one is to prevent a random number from equaling zero since the value of zero is not associated with a NSN. For these reasons, this random number generation process provided an equally probable chance that any of the 10,969 NSNs could be selected for inclusion in the sample (20:1). As a result, 136 rank positions between 1 and 10,969 were identified. These rank positions were used to select the corresponding NSN from the CLSSA investment item listing obtained from SAMIS.

Once the 136 NSNs were selected, the following additional information was extracted from the SAMIS database:

1) requisition document number
2) requisition NSN
3) FMS case
4) requisition quantity
5) unit price of NSN
6) date requisition was received in SAMIS
7) requisition suffix code
8) CLSSA program/nonprogram code
9) master NSN applicable to the NSN cited in requisition

Analysis of the sample data revealed that only 99 of the 136 sample NSNs possessed valid demand history that could be used for forecasting purposes. Thirty-one of the sample NSNs (22.8 percent) were eliminated because they had zero demands over the ten year period. This finding is consistent with previous CLSSA investment item analysis. Prior analysis found that approximately 36 percent of all investment NSNs placed on the

CLSSA program have never been ordered (24:1). Six additional NSNs were eliminated because the only recorded demands resulted from customers attempting to terminate or reduce their previously established SLQ using drawdown requisitions requesting absorption. Drawdown requisitions requesting absorption are used to remove unwanted items and quantities from a participant's SLQ. Drawdown requisitions under this condition are not real demands by a customer and were accordingly excluded from the demand history. Drawdown requisitions requesting the items be shipped to the participant were treated as an actual demand for the item. This left 99 NSNs with valid demand data that could be used to test the forecasting models. Appendix A contains a list of the original 136 NSNs, a list of the NSNs with zero demands, a list of the drawdown requisitions removed, and a list of the remaining 99 NSNs with valid demands.

The histogram in Figure 2 identifies the demand frequency distribution for the remaining 99 NSNs. Each NSN was placed into one of three demand categories based on demand activity. Demand activity was defined as the cumulative number of requisitions received for the NSN from any CLSSA customer during the ten year period. The low demand category consisted of NSNs that had a demand frequency of just one or two demands over the ten year sample period. Thirty-five NSNs fell in the low demand category. These low demand NSNs were excluded from the forecasting comparison because the historical demand rates (one or two demands in ten years) reflect a lack of recurring demand. The stocklevel should only include NSNs with recurring demands (8:1-3). The CLSSA program does not require a method that will forecast for NSNs with nonrecurring demand. The only test performed on the low demand category concerned measuring how long the item remained on the stocklevel case before the model recommended a zero forecast. This analysis was only conducted against the AFSAC model to determine if the logic of rounding up, to a stocklevel of one for any value above zero and less than one, would significantly increase the stocklevel value. The medium

demand category included NSNs with a demand frequency range from 3 to 34 demands. Fifty-one NSNs fell into the medium demand category. The high demand category included NSNs with a demand frequency range from 35 to 210 demands. Thirteen NSNs fell into the high demand category.

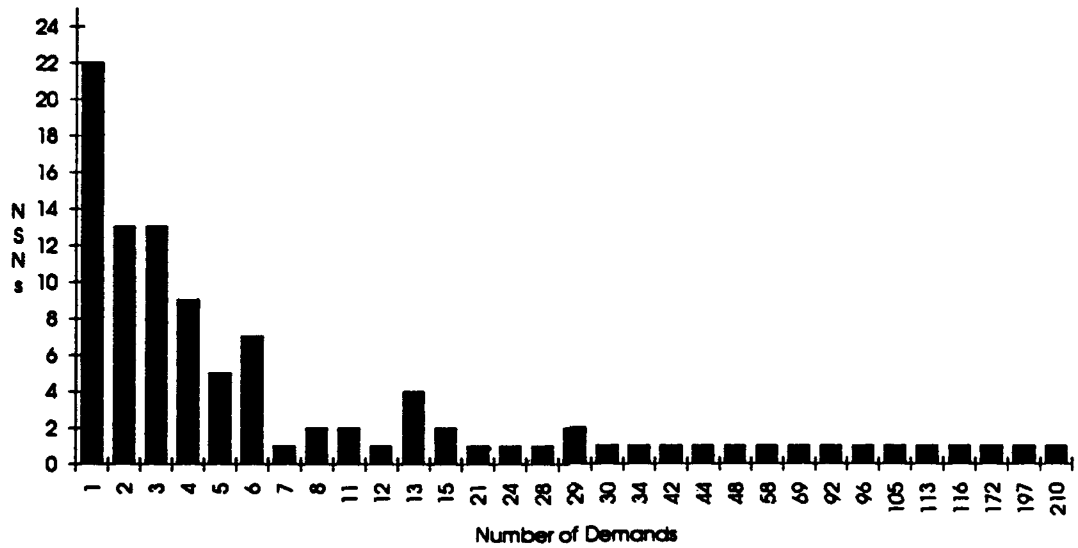

Figure 2. Histogram of Sample Population

Model Selection

Previous research has established that no one forecasting method works best in all circumstances. As a result, forecasters must select the technique which works best for their particular requirements based upon the presumed patterns in the data (13:7-23). Based on the information examined in the literature review concerning various forecasting methods, three traditional forecasting models were selected that previous research had shown to be the most accurate in responding the patterns hypothesized to exist in CLSSA

historical demand data (13:13). A fourth model, the AFSAC retention formula, was selected. The AFSAC model was selected to measure its accuracy in comparison to other potential CLSSA forecasting methods. The AFSAC intends to implement its retention formula in October 1994. As such, the retention formula serves as a standard to measure the performance of the traditional models.

Using the times-series criterion alone resulted in the selection of the double exponential smoothing model (13:70-73; 14:79-80; 15:55-60). Two additional models, the adaptive response and the classical decomposition models were selected based on their ability to enhance a time-series forecast using underlying trends, cycles, and seasonality. It was anticipated that a trend would exist as a item passed through its life cycle (23:32). Cycles and seasonality were postulated to exist due to disparities in the FMS customers' fiscal year, exercise participation, flying hour profiles, and holiday seasons. Analysis and rationalization of these trends, cycles, and seasonality factors was expected to lead to more accurate forecasts. The adaptive response model excels in its ability to identify and effectively respond to changes in underlying data patterns (13:82-96; 14:266-274; 15:286-299). The classical decomposition model excels in its ability to separate the data into the individual subparts of trend, cycle, and seasonal changes (13:171-196; 14:383-387; 15:328-361).

Forecasting Methods Evaluated

Four forecasting methodologies were evaluated to determine which method produced the most accurate forecast of CLSSA reparable item demands. These methods consisted of the three traditional and one unique method developed by the AFSAC. A description of the forecasting methods evaluated follows:

Double Exponential Smoothing - This method in concept is similar to the double

moving average method. In this method, a single exponential smoothed value is calculated. Next, a double exponential smoothed value is calculated using the single exponential smoothed values as input. The difference between these two calculations is added back to the single smoothed value for a forecast value. Double exponential smoothing produces more accurate results than single exponential smoothing when trend patterns exist in the data. Research has found that the double exponential smoothing method always produces more accurate results than the double moving average method (13:70-73; 14:79-80; 15:55-60).

Classical Decomposition - Most time series methods attempt to produce forecasts by accounting for the cumulative impacts of trend factors, cyclical factors and seasonal factors. The decomposition method separates the overall data pattern into individual subparts of trend, cycle and seasonal elements. This method can be used to explain fluctuations in data values and permits predictions to be tailored to reflect trend, cycle and seasonal changes (13:123-145; 14:198-209; 15:88-138).

Adaptive Response - This method uses weighted historical data to forecast future values. The value of the weight applied to each historical data value is recalculated for each new forecast period. The amount of adjustment to the weights is based upon the amount of error that occurred between the previous period's forecast value and actual value. This is a dynamic method where the weights will be continuously adjusted. The adaptive capability of this method permits it to respond effectively to changes in the patterns of the underlying data. This method usually produces more accurate results than the moving average and exponential smoothing methods; especially when the historical data contains a complicated underlying pattern (13:82-96; 14:266-274; 15:286-299).

AFSAC Retention Formula - This method segments the four year demand history of each CLSSA investment item into a repair (requisitions containing an "H" in card column 40 of the FMS requisition) and nonrepair component. The algorithm described

below is applied to each of the demand segments (repair and nonrepair) to predict consolidated future demands. On the first day of each quarter the model examines the past four year period (16 quarters) for recurring demands (requisitions submitted by the FMS customer with an "R" in card column 44). These demands are then placed into their respective 16 quarters. Weights are then assigned to place emphasis on the most recent data. To determine a weighted quantity, the sum of each quarterly quantity is multiplied by a weighting factor. This weighting factor starts at 100 percent, and is reduced by 6.25 percent each time a zero quantity exists for a quarterly sum. After the weighting factor has been assigned to each quarter, the actual quarterly demand is multiplied times the weighting factor to arrive at a weighted quantity. All sixteen of these weighted quantities are summed for a total weighted quantity.

The total weighted quantity is then divided by the number of years involved in the accumulation of demands. The number of years involved in demand accumulation is determined as follows: if there are demands in quarters 13-16, then the number of years equals 4, and the total weighted quantity should be divided by 48 to arrive at a total monthly demand quantity. If all the demands in quarters 13-16 are zero, but there are demands in quarters 9 -12, then the number of years equals 3, and the total weighted quantity should be divided by 36 to arrive at a total monthly demand quantity. If the demands in quarters 9-16 are zero, but there are demands in quarters 5-8, then the number of years equals 2, and the total weighted quantity should be divided by 24 to arrive at a total monthly demand quantity. Finally, if the demands in quarters 5-16 are zero, then the number of years equals 1, and the total weighted quantity should be divided by 12 to arrive at a total monthly demand quantity.

For nonrepair demands, the stocklevel quantity is the monthly demand quantity times the lead time in months. For repair demands, the stocklevel quantity is the repair time in months plus a six month additive for administrative processing time. If the total

monthly demand value is less than one for either the repair or nonrepair demand segments, the value of each is rounded up to one. All other values less than .5 are rounded down and values of .5 or above are rounded up to the next whole number. The resultant total monthly demands for the repair and nonrepair components are then summed. The summed value is than multiplied by three to arrive at a quarterly value for forwarding to the item manager via DO41 (21:1).

Demand Segmentation

Demand for each NSN is a combination of two types of demand. The first type demand is where the CLSSA customer receives a serviceable asset in exchange for a reparable carcass, referred to as repair/replace support. The second type demand is for an additional item without exchanging a reparable, referred to as nonrepair support. Thus, the total demand for each NSN was segmented into three categories: 1) combined repair/replace and nonrepair demands, 2) repair demands only, and 3) nonrepair demands only. This segmentation process was necessary in order to provide an equitable comparison of the traditional forecasting methods with the AFSAC retention formula. The AFSAC retention formula calculates repair support demands differently than nonrepair support demands. Repair support consists of demands that include the CLSSA customer returning a reparable carcass to a US depot for repair. In this situation the customer receives a serviceable asset from US depot stock in a relatively short period. For this thesis, these demands are called 'H-coded' demands and are considered to have an average repair time of 9 months. Nonrepair support consists of demands where no reparable carcass will be returned. In this situation, the depot replenishment time equates to the procurement lead time for the item. These lead time are significantly longer that repair replenishment. For this thesis, these demands are called 'N-coded' demands.

Nonrepair item forecasts were calculated based on two standardized lead times: one at 24 months to reflect an item that has a short to medium lead time and one at 36 months to reflect an item with a medium to long lead time.

Forecasting Process

Forecasts were produced under four different forecasting horizons. These horizons were for: 1) one quarter, 2) one 24 month lead time, 3) one 36 month lead time and, 4) one 9 month lead time. The one quarter forecast was intended to provide an initial performance comparison among the three traditional forecasting methods. The 24 month lead time forecast was selected to represent the forecasting horizon of interest for a short to medium lead time item. The 36 month lead time was selected to represent the forecasting horizon of interest for a medium to long lead time item. The 9 month lead time was selected to represent the forecasting horizon of interest equating to repair lead time item. The repair lead time period is analogous to the lead time experience when a CLSSA customer returns a reparable carcass at the same time a replacement item is demanded.

Results of the forecasting process were evaluated at 9, 24, and 36 months because effective forecasting must match the characteristics of the situation or process at hand with the characteristics of the forecasting methodology (13:33). These lead times represent the forecast horizon of interest. The longer the forecast horizon, the greater probability for error (16:445). Assessing each model at the various lead times measures the degree of accuracy deterioration. An investigative question was to determine which model was the most accurate. Overall accuracy is a function of the model's capability to produce accurate forecasts over a range of forecasting horizons. For this research, forecasting

horizons of 9, 24 and 36 months were selected as being representative of various CLSSA horizons.

The lead time of an item is important to the CLSSA program because it determines the length of the forecasting horizon. The CLSSA stocklevel quantity should represent the quantity of items that should be in inventory to support recurring demands that occur over the lead time of the item. The longer the lead time, the longer the forecast horizon. Forecasting methods become increasingly inaccurate as the forecasting horizon increases. Measuring forecast accuracy for various lead times required the model to forecast for various time horizons. Any CLSSA forecasting method must be capable of accurately forecasting across a range of lead times. A method that may produce extremely accurate results for a short horizon may produce extremely inaccurate results for a long horizon. This methodology permitted accuracy measurement to be assessed based on performance across a range of horizons rather than just one specific horizon. This method attempts to reflect the actual lead time variability of the CLSSA environment.

As previously stated, the demand for each NSN was segmented into categories. This categorization permitted analysis of each of the forecasting methods' ability to forecast for each of three segments of CLSSA demand. The first category represents the cumulative CLSSA demand for the particular NSN. This category combines demand both for repair support as indicated by H-coded requisitions and for nonrepair support as indicated by N-coded requisitions.

The second category represented H-coded only demands for the NSN. This category represents demands that were submitted in accordance with repair/replace procedure. These types of demands can be distinguished by a "H" in the requisition document number. These types of demands are referred to as "H-coded" demands. H-coded requisitions are different from a regular requisitions in that the customer agrees to return a reparable carcass to the appropriate US depot in return for being supplied a

serviceable item. H-coded demands theoretically have a shorter lead time relating to the average repair time for the item versus the full procurement lead time. Because of this lead time difference, each forecasting method's ability to respond to this distinct type demand pattern was tested.

The third segmentation involved aggregating all the 'regular' demand requisitions. This category referred to as 'N-coded only' demands represents all demands not submitted under the repair/replace program. N-coded demands represent requirements for material when a reparable carcass will not be provided to the US depot for repair. Material must normally be procured to support these requirements.

As a result of the demand segmentation process, three data streams existed for each NSN. These data streams were comprised of 1) the cumulative H-coded and N-coded demands for the NSN, 2) only the H-coded demands for the NSN and, 3) only the N-coded demands for the NSN. Each forecasting model was examined using each of these data streams as input.

Forecasting Software

Forecasts for the three traditional methods (double exponential, adaptive response and classical decomposition) were computed using the *SORITEC Sampler II Version 6.4.035* forecasting software package (26). This is a special educational version of the SORITEC commercial forecasting package that is used by many well known financial institutions, government agencies, public utilities, industrial firms and academic institutions (25:viii). The key difference between the commercial version and the sampler version is that the sampler version does not include the full complement of report generation capabilities. The SORITEC Sampler package automatically calculates the optimal

smoothing value of alpha for exponential smoothing, beta for adaptive response and the linear trend and seasonal indices for classical decomposition.

The AFSAC retention formula applies a complex weighted average algorithm to produce CLSSA forecasts. Due to the unique and elaborate weighting scheme and to increase validity, AFSAC was requested to produce forecasts for the sample data rather than attempt to replicate their retention formula code. AFSAC graciously agreed to run the sample data through their algorithm on their hardware.

AFSAC's retention formula operates on 16 quarters of the most recent historical demand history for each NSN. The model uses this data to forecast one lead time into the future. A total of 25 data streams consisting of 16 sequential quarters could be generated from the sample's 40 quarters of data. For example, the first data stream included demands from the 16 quarters from 1984 quarter 1 through 1988 quarter 4. The second data stream then included the 16 quarters of data from 1984 quarter 2 through 1989 quarter 1. An example of the format of the data provide AFSAC is in Appendix C.

To be consistent with the forecasting process established for the three traditional methods, the AFSAC was provided with three different aggregations of the demand data for each NSN. The first aggregation consisted of the combined H-coded and N-coded demands. The second aggregation grouped the H-coded only demands and the third aggregation provided the N-coded only demands. This approach, like that for the other forecasting methods, permits evaluation of the model's accuracy in responding to three different data pattern inputs.

One Quarter into the Future

A one quarter into the future forecast was accomplished to provide an initial evaluation of the three traditional forecasting methods among one another. The AFSAC

retention formula could not be used in this comparison. The sample data was segmented into chronological quarters based upon the date that each individual requisition was received by SAMIS. The ten years of sample data produced 40 quarters of demand data. The 40 quarters of demand data were further segmented into three categories of CLSSA demand. As a result of the segmentation process, three data streams existed for each NSN. These data streams were comprised of 1) the cumulative H-coded and N-coded demands for the NSN, 2) only the H-coded demands for the NSN, and 3) only the N-coded demands for the NSN. Each of these data streams for each NSN in the sample were provided as 40 quarters of historical input data to each of the three traditional forecasting models. As a result, each method produced a total of three forecasts for each NSN. Each forecast was rounded to a whole number using standard rounding rules of .50 or greater being rounded up and .49 or less being rounded down. Forecasts of negative values were rounded to zero.

Twenty-four Month Forecasts

The 24 month (8 quarters) forecasts were accomplished by reaggregating the 40 quarters of historical demand data into 24 month units. This reaggregation could have been in any unit period. However, aggregating the data into input units that correspond to the forecast horizon simplifies the forecast process. By providing data inputs in the same unit period as the forecast horizon, the forecasting models simply produce a forecast for one period into the future. No conversion of model output is required to generate a prediction for the forecast horizon. For example, if quarterly data was used as input, the output would also be in units of quarters. This output would require an arithmetic process to generate a forecast for the 24 month period of interest. An example of a 24 month lead time forecast input is located in Appendix C.

The 40 quarters of historical data converted to 33 values. Each value represented the cumulative demand for an individual 24 month period. These 33 units of demand data were input to each of the traditional forecasting models. The AFSAC retention formula, regardless of the forecasting horizon, required 16 quarters of historical data to initialize prior to producing its first forecast. The double and single exponential models required one demand value to initialize before providing the first forecast value.

One lead time of actual historical demand had to be reserved to measure the accuracy of the final forecast. For the 24 month forecasts, the final 8 quarters of data (1992 quarter 1 through 1993 quarter 4) were reserved for accuracy measurement. As a result of the initialization and accuracy reserve data requirements, a maximum of 17 measurable observations were possible for the AFSAC retention formula.

The 24 month comparable forecast horizon was limited by the AFSAC model which could only forecast a maximum of 17 lead time periods from 1988 quarter 1 through 1991 quarter 4. For each forecasting method, an average MSE was computed by summing the MSE values from each NSN forecast and then dividing by the number of NSNs that the method could produce a forecast. For example, if a forecasting method could produce a forecast for 63 of the 64 sample NSNs, the MSE values from each of the 63 forecasts would be summed and then divided by 63 to yield an average MSE for that forecasting method. In order to fairly compare the traditional forecasting methods' performance to the AFSAC method's performance, the results from the same forecast periods must be measured. The MSE comparison results are from AFSAC's maximum measurable 17 periods.

Thirty-six Month Forecasts

The 36 month (12 quarters) forecast was accomplished by reaggregating the 40 quarters of historical demand data into 36 month units. An example of a 36 month lead time forecast input is located in Appendix C. The 40 quarters of historical data converted to 29 units of individual 36 month demand values. These 29 units of demand data were input to each of the traditional forecasting models.

The AFSAC retention formula, regardless of the forecasting horizon, requires 16 quarters of historical data prior to producing its first forecast. One lead time of actual historical demand had to be reserved to measure the accuracy of the final forecast. For the 36 month forecasts, the final 12 quarters of data (1991 quarter 1 through 1993 quarter 4) had to be reserved for accuracy measurement. As a result of the initialization and accuracy reserve data requirements, a maximum of 13 measurable observations were possible for the AFSAC retention formula.

In order to fairly compare the traditional forecasting methods' performance to the AFSAC method's performance, the results from the same forecast periods must be measured. The MSE comparison results among all models are based on AFSAC's maximum measurable 13 periods running from 1988 quarter 1 through 1990 quarter 4. The same MSE averaging process used for the 24 month forecasts was used for the 36 month forecasts.

Nine Month Forecasts

The 9 month (3 quarters) forecast was accomplished by reaggregating the 40 quarters of historical demand data into 9 month units. An example of a 9 month lead time forecast output is located in Appendix D. The 40 quarters of historical data converted to

38 units of individual 36 month demand values. These 38 units of demand data were input to each of the traditional forecasting models.

The AFSAC retention formula, regardless of the forecasting horizon, requires 16 quarters of historical data prior to producing its first forecast. One lead time of actual historical demand had to be reserved to measure the accuracy of the final forecast. For the 9 month forecasts, the final 3 quarters of data (1993 quarter 2 through 1993 quarter 4) were reserved for accuracy measurement. As a result of the initialization and accuracy reserve data requirements, a maximum of 22 measurable observations were possible for the AFSAC retention formula..

Again, in order to fairly compare the traditional forecasting methods' performance to the AFSAC method's performance, the results from the same forecast periods must be measured. Therefore, the MSE comparison results are from AFSAC's maximum measurable 22 periods running from 1988 quarter 1 through 1993 quarter 1. The same MSE averaging process used for the 24 month and 36 month forecasts was again used for the 9 month forecasts.

Performance Measurements

Because of the inherent inability of any model to produce a completely accurate forecast, a quantitative process must be used to evaluate the degree of accuracy achieved by each forecasting method. The forecasting model that produces the smallest forecast error over the range of sample data was selected as the 'best' model. Forecast error is the difference between the observed historical value and the predicted forecast value. If the individual forecast errors are random, as they should be if the choice of the forecasting method is appropriate, some errors will be positive and some errors will be negative. Simply summing each individual error would then result in an error sum near zero.

Squaring the individual forecast errors then averaging these squared errors over the number of observations avoids this problem. This average of the squared errors is commonly referred to as the mean squared error (MSE). The forecasting method which produced the smallest MSE is considered to be the most accurate.

The mean percentage of error (MAPE) could not be used as a performance measure for this data. The MAPE is the percentage that results from dividing the absolute error from the forecast by the actual value that subsequently occurred for that same period. The sample data frequently had zeros as the actual values. MAPE would have required division by zero in these instances which is not possible.

In order to provide some perspective of each method's performance in terms of actual number of items of error, the square root of the MSE is presented. The square root of the MSE serves to translate the MSE into a more intuitively understood measurement.

The most relevant categories to compare accuracy are the N-coded 24 and 36 month categories and the 9 month H-coded categories. The reasons these are considered to be the most relevant measurement categories are 1) the new CLSSA program will use separate H-coded and N-coded forecasts to compute stocklevels, therefore, the combined categories are not relevant measures, 2) N-coded requirements have longer lead times relating to the 24 and 36 month measurements, and 3) the H-coded requirements have shorter lead times relating to the 9 month measurements.

Cost Measurements

Since forecasting is concerned with predicting the demand for a specific item based on the historical demand patterns without regard the cost of the demand, a direct relationship between model performance and cost could not be established. Three measurements were used to answer the investigative question regarding the financial

impact of each model's performance on the value of the FMSO I case. These three financial measurements ranged from a generalized to a specific measurement.

The first and most generalized financial measurement simply takes the total value of all the demands divided by the total number of demands to arrive at an average value per item. This average value per item was multiplied by the quantity of items predicted by each model to generate a FMSO I value associated with each model.

The second financial measurement calculated an average value for each item within the low, medium, and high category. To determine the average value by category a total demand value was calculated for each NSN, these values were summed based on the NSN category, and then divided by the total number of demands within the category. The result was an average value for each item within a demand category. This average category value was used to assess which model category attributed the most financial impact on the FMSO I value.

The third and most specific financial measurement was calculated by taking the total value of all the demands for a particular NSN divided by the number of demands received to arrive at an average cost per NSN. The average cost per NSN was multiplied by the forecast quantities to arrive at a new FMSO I value. At the latest date where all models could generate a forecast, the cost performance measurements were compared to the actual demands and the current FMSO I value to determine the financial impact each model had on the FMSO I case.

Validity

The sample data consisted of actual historical CLSSA demands placed over a ten year period. Given that the final usable sample size was large (99 NSNs), it was appropriate to assume that the data display typical demand patterns that are present in the

population. The methodology examines how each of four forecasting methods performs on these various data patterns. The age of the sample data would not be a significant factor that influences the results, since, the low, medium and high demand categories permitted the use of potentially outdated data to make generalizations on current demand trends because all demand rates for CLSSA NSNs will fall into one of these categories. NSNs may over time change from one demand category to another throughout the item's life cycle. Therefore, if a large sample of historical NSN demand data can be used to develop accurate forecasting methods for each demand category, then these same forecast methods should be accurate for future demands in the same category regardless of the particular item.

The SORITEC software package was used to compute the forecasts for the three traditional methods (26). The forecasting algorithm code within this software has been tested and can be considered reliable. The AFSAC forecasts were computed using the actual algorithms and hardware that will be used for actual CLSSA processing as of 1 October 1994. The use of these sources for calculating the forecasts contributes to the validity of the results.

Study Limitations

The results of this research are limited in use to the current mix of FMS customers and the weapon systems being supported. The budget constraints being experienced in the foreign governments may result in reduced operational requirements and effect the results of the forecasting models. Modifications to the forecasting model may be required as the FMS customers' mix of weapons systems supported evolve.

IV. Results and Analysis

Overview

This chapter contains the results obtained from the methodology described in Chapter Three. The results are discussed based upon chronological progression of the research. This section begins with a discussion of the results obtained when forecasting just one quarter into the future. These results lead to a redefinition of the forecasting horizon. Difficulties encountered in the one quarter into the future forecast generated revisions to the original methodology. Rationale for revising the methodology is described. Next, the results obtained for the 24, 36, and 9 month forecasts produced under the revised methodology are presented. Finally, an analysis of the results is provided by providing answers to each of the investigative questions based upon the results achieved from this research.

One Quarter into the Future Forecast

The objective of this initial comparison was to produce a summary assessment of the three traditional models' (double exponential, adaptive response, classical decomposition) ability to perform when provided 40 quarters of actual CLSSA demand history as input. The AFSAC retention formula was not used in this initial comparison. Each traditional method computed forecasts using the same 40 quarters of input data. In this process, each model could use actual quarter 1 data to forecast for quarter 2 demand, then use actual quarters 1 and 2 to forecast for quarter 3. This process continued so that for the final quarter, the program could use actual data from quarters 1 through 39 to forecast quarter 40 demand. The results examined which of the three traditional methods

would produce the most accurate result as measured by their respective mean squared error (MSE).

The results of the one quarter into the future forecasts are provided in Appendix D. The abbreviation "No Comp." means that the SORITEC software was unable to arrive at an optimal smoothing value for alpha or beta based upon the time-series data provided as input. As a result, a forecast could not be generated.

Table 1 presents a summary of the cumulative MSE for each NSN in each of the three demand categories (Total H & N Coded Combined, H-Coded Only, N-Coded Only). The double exponential method produced forecasts for 80 percent of the combined demands, 60 percent of the H-coded only demands and 80 percent of the N-coded only demands. The adaptive response model performed much worse. This model could only produce forecasts for 37 percent of the combined demand, 26 percent of the H-coded only demand and 21 percent of the N-coded only demand. The inability of the software to identify a optimal smoothing value using either double exponential or adaptive response methods would be a significant hindrance to implementing either of these two methods.

Based upon this poor performance, the adaptive response was eliminated from further consideration and testing. Its inadequacy to consistently provide forecasts make it impractical for actual application regardless of the degree of accuracy achieved. Cursory analysis suggests that erratic demand spiking caused the software's algorithm to be unable to compute an optimal smoothing value for the adaptive response method. This finding is consistent with the literature review which states that the adaptive response method does not perform well when there is significant seasonality in the data. Although irregular, the spikes that appear in the data are similar to seasonal spikes. The double exponential method, although performing much more consistently, would also require an additional forecasting method to produce a default forecast when the double exponential method could not compute one.

TABLE 1

One Quarter Into the Future Forecasts

	H&N Coded Combined			H-Coded Only			N-Coded Only		
	Double Exp.	Adaptive Rate Exp. Smooth	De-comp	Double Exp.	Adaptive Rate Exp. Smooth	De-comp	Double Exp.	Adaptive Rate Exp. Smooth	De-comp
MSE Sum	2795.1	2325.7	1580.8	253.5	1341.99	219.30	2856.42	1584.33	1154.9
Observations	52.00	24.00	65.00	39.0	17.00	65.00	52.00	14.00	65.00
Average MSE	53.75	96.90	24.32	6.5	78.94	3.37	54.93	113.17	17.77
Pct Function	0.80	0.37	1.00	0.60	0.26	1.00	0.80	0.22	1.00

The classical decomposition model clearly performed the best of the three traditional methods. Its MSE was the least for each of the three demand categories and it performed 100 percent of the time. The forecasts produced by this method were based upon a SORITEC computed trend line and seasonal index factor calculated from the historical data. However, the cyclical component of the forecast could not be automatically computed by SORITEC. SORITEC requires external input for cyclical factors across the forecast horizon. For the purposes of this research, a judgmental forecast of the cyclical component value was used in computing the next quarter's forecast. The judgmental forecast was derived from graphical review of the trend factors and of the historical cyclical component line. Based upon this method's performance in the one quarter forecast, it was selected for further analysis and testing against the AFSAC retention formula.

Limitations to the One Quarter Forecast

Initial forecasts one quarter into the future provided valuable information; however, they did not address the ability of the methods to accurately forecast demand for the horizon required by the CLSSA program. The CLSSA program needs forecasts of

future demands in order to establish stocklevels for each NSN. A stocklevel represents the quantity of an item that must be available to meet demands that occur between the point in time when stock replenishment action is initiated and the point in time when the replenishment material is delivered to the depot. The length of this period of time, referred to as lead time, will vary for each individual NSN. To provide effective CLSSA support and to control CLSSA inventory investment costs, a forecast of the demand that will occur over this future lead time period is required. Action to adjust the on-hand or on-order materiel will be taken dependent upon the forecast. If the forecast predicts demand during the lead time to be greater that the current stocklevel, action to procure additional materiel will be required. If the forecast predicts demand during the lead time to be less than the current stocklevel, action will be taken to liquidate the excess portion to the stocklevel.

The research tested the forecasting methods' accuracy in predicting demand over standardized lead times. The combined H & N coded category and the N-coded only category were examined at two lead times; one at 24 months (8 quarters) and the other at 36 months (12 quarters). The lead times were selected to represent items with a short to medium lead time (24 months) and a medium to long lead time (36 months). The H-coded only items were examined at one lead time of 9 months (3 quarters). This lead time represents the period of time required to obtain replenishment material from repair sources versus new procurement.

Forecasting for One Lead Time

Given the positive performance of the decomposition method in predicting one quarter into the future, similar results were anticipated using standardized lead times. Although very accurate when predicting one quarter into the future, the decomposition

method's performance was significantly different when attempting to make a prediction for a 9, 24 or 36 month lead time period. For the decomposition forecasting procedure, SORITEC was provided 16 quarters (4 years) of historical data for initialization and establishment of a linear trend line and seasonal index. A sixteen quarter of initialization period was selected because it equates to the same initialization period used by the AFSAC retention formula. Again, the SORITEC program required external inputs of the cyclical component factors. Attempts to make these judgmental forecasts for the cyclical component 9, 24 or 36 months into the future proved to be quite tedious and time consuming. The cyclical component of the decomposition model was subsequently eliminated because the underlying causal factors for the cycle could not be identified. Unless an automated process could be identified to calculate a cyclical component factor for each NSN, the use of a cyclical factor in forecasting across the population of 10,969 CLSSA NSNs is impractical.

Following the elimination of the cyclical component, the decomposition forecast consisted of a trend component and a seasonal index component. The decomposition method computed a trend line that incorporated inputs from all demands that appeared in the 16 quarters of historical initialization data. Erratic demand spiking frequently caused the trend line slope to be inappropriately skewed. For example, if a NSN's ten year demand pattern had the majority of quarterly demand in the range of 1 to 10 but also had a few quarters early in the ten years with demands of 100, a negative slope would be calculated when in actuality the overall demand was fairly stationary. Once the slope of the trend line was calculated, the SORITEC program projected that same slope over the specified number of periods into the future. For decreasing slopes, the trend line would frequently cross the zero value on the x-axis after just 4 to 6 quarters into the future. The trend line would continue into the negative region for the balance of the forecast period. This resulted in trend components being computed as large negative values. The reverse

of this condition occurred when the large quantity spiking had transpired latter in the demand pattern. In this situation, a positive trend line would continue to grow at a constant rate over the entire forecasting horizon. The trend component value for the latter periods of the forecast horizon became relatively large compared to the values from the 16 quarters of historical initialization data.

The problems encountered with the trend line were further compounded by the seasonal index component. The intent of the seasonal index is to either inflate or deflate the forecasted values to correspond to historical seasonal fluctuations in demand. Seasonal index weights are used as an adjusting factor to the underlying forecast value. Application of the weight presumes that the underlying forecast value is correct within the required limits. The analysis identified that the trend component of the forecast was generally grossly erroneous, the seasonal index, when greater than one, further increased the magnitude of the forecast error.

No consistent seasonal index pattern occurred. Each NSN had a unique index that reflected the peculiarity of the particular historical demand. This feature of the decomposition model would be useful, if the forecast horizon period were to focus on some quarterly subset of a year. However, if the forecasting horizon extends across multiple years, the benefit of producing seasonally adjusted quarterly forecasts is basically negated. The negation results because the seasonal weights applied within any one year always sum to four. In this situation, the increasing weight applied to a particular quarter is, in part, canceled out by the decreasing weight applied to a different quarter within the same year. The forecasting horizon extended across multiple units of whole years, two years for the 24 month standardized lead time and three years for the 36 month standardized lead time. In this situation, the seasonal index, even if applied to a valid underlying forecast, was of little practical benefit.

Gross inaccuracies of the decomposition model can be attributed to a constant trend line being forced upon data that did not possess a trend. As illustrated in Appendix B, the majority of the data does not exhibit trend patterns. Due to the inaccuracies and inability of the model to identify the causal factors necessary to utilize the cyclical component, the decomposition method was eliminated from further consideration and testing.

Rationale for Revised Methodology

Based upon the disappointing experience with both the adaptive response method (inability to forecast from the demand pattern) and the decomposition method (inability to use the cyclical component and gross inaccuracies), the original methodology was revised. Given the failure of two of the three initial traditional models, four additional, simplistic traditional methods were selected for testing along with double exponential smoothing and the AFSAC retention formula. The four additional traditional methods were single exponential smoothing, a two lead time moving average, a three lead time moving average and a four lead time moving average. These additional models were selected because their simplistic calculation approach presented a high probability that the SORITEC program would produce forecasts in spite of the demand spikes. The intent in testing additional methods was to provide a range of forecasts results to compare against double exponential smoothing and the AFSAC retention formula.

Additionally, it was decided to reaggregate the demand data provided to each model. Under the revised methodology, each traditional model was provided historical demand data based in units of lead time rather than in historical chronological quarters. Reaggregating the input into lead time units of data was intended to smooth out the erratic spiking within the quarterly demand patterns. A NSN using the standardized 24 month

lead time had the quarterly demands revised to comprise moving summations of 8 quarters (24 months) of data. For example, if a NSN had demands of 5 for each of the first 8 quarters, the model was provided the single value of 40 rather than the eight individual values of 5. The five traditional forecasting methods were exercised using historical data aggregated on the basis of lead time to predict just one lead time period (9, 24, or 36 months) into the future.

The intention of this new method was to increase forecast accuracy. This procedure would result in each model forecasting only one period into the future. Because each model would be using demand data in the same units as the forecast horizon, it was anticipated that this approach would prevent the models from inappropriately focusing on short term quarterly changes in the data. This research was not interested in generating forecasts that would following the radical changes between quarters. Instead, it was interested in forecasting the cumulative demand over an entire lead time period. Furthermore, the literature review repeatedly stated that forecasts become progressively more inaccurate over a longer periods into the future. The initial forecast approach was attempting to forecast multiple quarters into the future: for example, 8 quarters for the 24 month standardized lead time and 12 quarters for the 36 month standardized lead time. Using the new approach, the forecast was only necessary for one period into the future.

Accuracy Measurement

The accuracy of each model was measured for each of the 13 NSNs in the 'high' demand category and 51 NSNs in the 'medium' category. The accuracy was measured by summing the value of the MSE for each measurable observation produced by the given forecasting model. An average MSE was then calculated for each NSN by dividing the

sum of the individual MSE values by the number of measurable observations for the particular NSN. An average MSE for the forecasting method was calculated by summing the average NSN MSE and dividing by the number of NSNs. The average MSE for each forecasting method provided a general indication of each method's accuracy.

However, when comparing competing models, the average MSE was adjusted to correspond to the model with the lowest number of measurable observations. In each of the forecasting horizons (24, 36 and 9 months), the AFSAC retention formula produced the least number of measurable forecasts. Therefore, the accuracy of all models was compared based upon the AFSAC's maximum forecasting horizon capabilities. For the 24 month forecasts, comparisons were based on the 17 periods from 1987 quarter 4 to 1991 quarter 4. For the 36 month forecasts, comparisons were based on the 13 periods from 1987 quarter 4 to 1990 quarter 4. The 9 month comparisons were based on 22 periods from 1987 quarter 4 to 1993 quarter 1.

Twenty-four Month Forecasts

For the 24 month combined H and N-coded forecasts, the SORITEC program was unable to produce a forecast for 1 of the 64 NSNs using both the double and single exponential methods. The results of the combined H and N-code forecasts are presented in Table 2. The range of forecast error for the combined H and N-coded forecasts runs from AFSAC's retention formula being the 'best' at a MSE of 658.49 to double exponential smoothing being the 'worst' at a MSE of 825.78. The real magnitude of the difference when compared in whole units of items, by rounding the square root of the MSE, becomes +/- 26 items for the AFSAC retention formula and +/- 29 items for the double exponential formula. The four period moving average method was a close second being just three percent less accurate than the AFSAC retention formula.

TABLE 2

Comparison of Combined H & N Code 24-Month Forecasts

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
MSE Sum	52024.18	47138.94	46045.71	44936.94	43546.00	42143.70
Observations	63.00	63.00	64.00	64.00	64.00	64.00
Average MSE	825.78	748.24	719.46	702.14	680.41	658.50
Sq. Root MSE	28.74	27.35	26.82	26.50	26.08	25.66

Analysis of the MSE by individual NSN identified that the majority of the error could be attributed to just a few items. Five items, NSNs H3, H6, H9, H10, and M51, cumulatively produce between 70 to 84 percent of the total error for each of the forecasting models. Table 3 shows this comparison. NSNs H3, H6, H9, H10, and M51 represent demand patterns that none of the methods were capable of responding to well. The data pattern for these items is provided in Appendix B. With these large sources of error removed, the AFSAC retention formula and the double exponential smoothing produced essentially the same degree of accuracy (+/- 12 items) with MSEs of 143 and 142 respectively.

TABLE 3

Comparison of Combined H & N Code 24-Month Forecasts Excluding Five NSNs

NSN Excluded	Percent Double Exp.	Percent Single Exp.	Percent Moving Average 2	Percent Moving Average 3	Percent Moving Average 4	Percent AFSAC Method
H3	0.13	0.11	0.11	0.11	0.10	0.06
H6	0.23	0.22	0.22	0.21	0.20	0.15
H9	0.12	0.12	0.12	0.13	0.13	0.11
H10	0.06	0.06	0.05	0.05	0.05	0.05
M51	0.30	0.29	0.29	0.29	0.29	0.43
Cumulative	0.84	0.80	0.79	0.79	0.78	0.80
Revised Avg. MSE	142	163	162	162	162	143
Revised Sq. Root	11.91	12.76	12.72	12.74	12.74	11.96

The results of the N-coded only demand patterns are provided in Table 4. The lower number of observations for the N-coded only forecast was primarily caused by a lack of N-coded demand for several on the sample NSNs. Furthermore, SORITEC could not compute forecasts for 4 NSNs using the double exponential algorithm. Additionally, AFSAC forecasts were not computed for four NSNs.

TABLE 4

Comparison of N-coded Only 24-Month Forecasts

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
MSE Sum	43042.12	40002.[illegible]7	38578.29	37672.94	36645.88	41537.12
Observations	51.00	55.00	55.00	55.00	55.00	51.00
Average MSE	843.96	727.32	701.42	684.96	666.29	814.45
Sq. Root MSE	29.05	26.97	26.48	26.17	25.81	28.54

Unlike the combined H and N-coded forecasts, the four period moving average produced the lowest average MSE. The AFSAC and double exponential methods respectively had the highest and next to highest average MSE. The difference between the combined H and N-coded category and the N-coded only category forecast is caused by a different demand pattern existing for the N-coded only data.

Again, just a few items could be identified as contributing the major portion of the overall forecasting error. NSNs H3, H6, H9, H10, and M51 comprised between 84 to 93 percent of the total forecast error. Table 5 shows this comparison. After the five most error prone demand patterns were removed from the average, AFSAC again produced the lowest MSE. NSN M51 alone produced between 28 to 44 percent of the error in the N-coded only forecasts.

TABLE 5

Comparison of N-coded Only 24-Month Forecasts

Excluding Five NSNs

NSN Excluded	Percent Double Exp.	Percent Single Exp.	Percent Moving Average 2	Percent Moving Average 3	Percent Moving Average 4	Percent AFSAC Method
H3	0.11	0.10	0.11	0.11	0.11	0.09
H6	0.30	0.28	0.28	0.28	0.27	0.28
H9	0.09	0.10	0.11	0.11	0.12	0.08
H10	0.08	0.08	0.06	0.06	0.06	0.05
M51	0.31	0.28	0.28	0.28	0.28	0.44
Cumulative	0.90	0.85	0.84	0.84	0.84	0.93
Revised Avg. MSE	94.73	119.61	121.17	120.76	120.83	64.36
Revised Sq. Root	9.73	10.94	11.01	10.99	10.99	8.02

Thirty-six Month Forecasts

The results from the combined H and N-coded 36 month forecasts are listed in Table 6. SORITEC was unable to produce a double exponential forecast for 3 NSNs and a single exponential forecast for 1 NSN. In this forecasting scenario, the four period moving average produced the 'best' forecast and AFSAC's formula delivered the 'worst' performance. The range of error, measured by the square root of the MSE, was noticeably larger for the 36 month forecast period versus the 24 month forecast period. The 36 month error ranges from +/- 31 items for the 'best' to +/- 37 items for the 'worst'.

TABLE 6

Comparison of Combined H & N Code 36-Month Forecasts

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
MSE Sum	66582.54	64741.15	63997.85	62645.62	60850.38	88933.92
Observations	61.00	63.00	64.00	64.00	64.00	64.00
Average MSE	1091.52	1027.64	999.97	978.84	950.79	1389.59
Sq. Root MSE	33.04	32.06	31.62	31.29	30.83	37.28

With the large error caused by the five NSNs, H3, H6, H9, H10 ,and M51 removed, as in Table 7, once again the AFSAC retention formula displayed the lowest MSE. The range of error was small; from 342 or +/- 18 items for the 'best' to 387 or +/- 20 items for the 'worst.'

TABLE 7
Comparison of Combined H & N Code 36-Month Forecasts Excluding Five NSNs

NSN Excluded	Percent Double Exp.	Percent Single Exp.	Percent Moving Average 2	Percent Moving Average 3	Percent Moving Average 4	Percent AFSAC Method
H3	0.07	0.06	0.07	0.07	0.07	0.05
H6	0.16	0.14	0.13	0.12	0.11	0.10
H9	0.11	0.11	0.11	0.11	0.11	0.08
H10	0.00	0.05	0.05	0.05	0.05	0.04
M51	0.34	0.30	0.29	0.29	0.28	0.50
Cumulative	0.68	0.67	0.65	0.64	0.63	0.77
Revised Avg. MSE	375.75	363.56	375.15	381.16	385.62	341.96
Revised Sq. Root	19.38	19.07	19.37	19.52	19.64	18.49

The results of the N-coded only demand patterns are provided in Table 8. The lower number of observations for the N-coded only forecast was again primarily caused by a lack of N-coded demand for several on the NSNs. Furthermore, SORITEC could not compute forecasts for 2 NSNs using the double exponential algorithm. Additionally, AFSAC forecasts were not computed for 4 NSNs.

TABLE 8
Comparison of N-coded Only 36-Month Forecasts

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
MSE Sum	57824.31	51622.38	50689.31	49180.00	47282.77	88491.76
Observations	53.00	55.00	55.00	55.00	55.00	51.00
Average MSE	1091.02	938.59	921.62	894.18	859.69	1735.13
Sq. Root MSE	33.03	30.64	30.36	29.90	29.32	41.65

The results from the N-coded only 36 month forecast was similar to the 24 month forecasts. All of the moving average methods out performed both the double exponential and the AFSAC retention formula. The four period moving average produced the lowest average MSE. The AFSAC and double exponential methods respectively had the highest and next to highest average MSE. The range of error in terms of items ranged from +/-29 items as the 'best' to +/-42 items as the 'worst.' The difference between the combined H and N-coded forecast and the N-coded only forecast is caused by a different demand pattern existing for the N-coded only data.

Again, just a few items could be identified as contributing the major portion of the overall forecasting error. NSNs H3, H6, H9, H10, and M51 comprised between 76 to 93 percent of the total forecast error. NSN M51 alone produced between 29 to 53 percent of the error in the N-coded only forecasts. Table 9 shows this comparison. After the five most error prone demand patterns were removed from the average, AFSAC again produced the lowest MSE. Here, the error in terms of items ranged from +/-12 items to +/-16 items.

TABLE 9

Comparison of N-coded Only 36-Month Forecasts Excluding Five NSNs

NSN Excluded	Percent Double Exp.	Percent Single Exp.	Percent Moving Average 2	Percent Moving Average 3	Percent Moving Average 4	Percent AFSAC Method
H3	0.04	0.05	0.06	0.06	0.07	0.04
H6	0.24	0.24	0.23	0.22	0.21	0.25
H9	0.11	0.11	0.12	0.12	0.13	0.06
H10	0.07	0.07	0.07	0.07	0.06	0.04
M51	0.33	0.31	0.30	0.29	0.29	0.53
Cumulative	0.79	0.78	0.77	0.77	0.76	0.93
Revised Avg. MSE	254.43	230.47	232.57	230.92	228.28	142.22
Revised Sq. Root	15.95	15.18	15.25	15.20	15.11	11.93

Nine Month Forecasts

The results from the H-coded only 9 month forecasts are listed in Table 10. SORITEC could not produce a double exponential forecast for 7 NSNs or a single exponential forecast for 1 NSN. Additionally, 13 NSNs had zero H-coded demands over the ten year sample period. In this forecasting scenario, the four period moving average produced the 'best' forecast and AFSAC's retention formula delivered the 'worst' performance. The range of error, measured by the square root of the MSE, was relatively small when compared to the error the 36 month and 24 month forecasts. The 9 month error ranged from +/- 6 items for the 'best' to +/- 9 items for the 'worst'.

TABLE 10
Comparison of H-Coded Only 9-Month Forecasts

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
MSE Sum	2393.91	2093.86	2117.27	2006.50	1854.36	4040.09
Observations	42.00	48.00	49.00	49.00	49.00	49.00
Average MSE	57.00	43.62	43.21	40.95	37.84	82.45
Sq. Root MSE	7.55	6.60	6.57	6.40	6.15	9.08

For the 9 month H-coded only forecast, almost half the error for the traditional forecasting methods can be attributed to just NSN H3. The AFSAC retention formula responded much better to this demand pattern with only 11 percent of the MSE error being attributed to H3, as depicted in Table 11. Unlike the 24 and 36 month forecasts, removal of the error caused by NSNs H3, H6, H9, H10, and M51 did not change the accuracy ranking of the methods. The four period moving average remained the 'best' and the AFSAC retention formula performed the 'worst'.

TABLE 11
Comparison of H-coded Only 9-Month Forecasts
Excluding Five NSNs

NSN Excluded	Percent Double Exp.	Percent Single Exp.	Percent Moving Average 2	Percent Moving Average 3	Percent Moving Average 4	Percent AFSAC Method
H3	0.55	0.47	0.45	0.45	0.43	0.11
H6	0.00	0.01	0.01	0.01	0.01	0.00
H9	0.03	0.05	0.05	0.06	0.06	0.02
H10	0.03	0.04	0.07	0.07	0.07	0.02
M51	0.06	0.06	0.05	0.06	0.06	0.01
Cumulative	0.67	0.63	0.64	0.64	0.62	0.16
Revised Avg. MSE	21.17	18.12	17.53	16.63	15.95	77.52
Revised Sq. Root	4.60	4.26	4.19	4.08	3.99	8.80

Forecast Error Distribution

In order to measure the overall the degree to which forecasting methods could accurately predict future CLSSA investment item demands, an analysis of the results which would have a direct effect on the FMSO I case were tabulated, summed and averaged. This produced quantified accuracy measurements for five forecasting models. These measurements identify which model forecasted the most accurately under five different categories of CLSSA demand scenarios. The scenarios tested were 1) at 24 months using combined H and N coded demands as input, 2) at 24 months using only N-coded demands, 3) at 36 months using combined H and N-coded demands, 4) at 36 months using only N-coded demands, 5) at 9 months using H-coded only demands. Table 12 presents the range of forecasting error measured. This error is in terms of the square root of the MSE. The square root of the MSE reports the error as the number of actual items. Therefore, the average error over the five CLSSA demand scenarios equates to +/-

5.8 items if all demand patterns are included, and +/- 3 items if the five demand patterns containing spiked demand are removed.

As evidenced in Table 12, the range of error as represented by the difference between the 'best' and the 'worst' forecast for each method. Overall, this average range is not great in terms of items. From this, it was concluded that the AFSAC retention formula's accuracy is approximately equal to that of the other forecasting methods.

TABLE 12
Range of Error Comparison Among All Methods

Method	Low Value	High Value	Range
24 Month H&N Combined	26	29	3
24 Month Combined (5 NSNs Excluded)	12	13	1
24 Month N-coded Only	25	29	4
24 Month N-coded (5 NSNs Excluded)	8	11	3
36 Month H&N Combined	31	37	6
36 Month Combined (5 NSNs Excluded)	18	20	2
36 Month N-coded Only	29	42	13
36 Month N-coded (5 NSNs excluded)	12	16	4
9 Month H-coded Only	6	9	3
9 Month H-coded (5 NSNs excluded)	4	9	5
AVERAGE RANGE ALL NSNs			**5.8**
AVERAGE RANGE (5 NSNs EXCLUDED)			**3**

The most relevant categories to compare accuracy are the N-coded 24 and 36 month categories and the 9 month H-coded categories. The reason these are considered to be the most relevant categories are 1) the new CLSSA program uses separate H-coded and N-coded forecasts to compute stocklevels, therefore, the combined categories are not relevant measures, and 2) high error forecasts cannot simply be excluded from consideration in actual CLSSA operation as was done for this research.

In considering only the relevant categories, the four period moving average was the most accurate in each category with an average error of +/- 20.43 items. Table 13 presents these results with a comparison to the AFSAC retention formula. The results are significantly higher than those shown in Table 12; however, modifications to the forecasting models to control high demand spikes would greatly improve the performance of either model. Although the improvement in accuracy is small, these results lead us to conclude that the four period moving average method is the most accurate in forecasting for the relevant categories of the sample CLSSA data.

TABLE 13

Error Comparison in Relevant Categories Only

Method	4 Period Moving Avg.	AFSAC Retention	Difference
24 Month N-coded Only	25.81	28.54	2.73
36 Month N-coded Only	29.32	41.65	12.33
9 Month H-coded Only	6.15	9.08	2.93
AVERAGE ERROR	20.43	26.42	6.00

Analysis of Results

The results of this research will be analyzed relative to the initial investigative questions and to the degree which the research provided the necessary information to answer them. Each investigative question is repeated below with a discussion of the findings.

1. How accurate are the forecasting methods in predicting future CLSSA demands?

This research measured the accuracy of each forecasting method using the MSE as the measure of accuracy. Tables one through sixteen present these accuracy measurements. The square root of the MSE provides a better estimate of accuracy in

terms of number of units error from the actual demand. On average, the forecasting methods predicted actual demands to with +/- 5.8 items. If the results of the 5 high error generating NSNs are removed from the computation, the forecasting methods predicted actual demands to within +/- 3 items. The most accurate method for forecasting in the relevant categories (N-coded only at 24 & 36 months and H-coded only at 9 months) was the four period moving average method.

2. To what extent, if any, will trends, cycles, and seasonality have on the accuracy of the forecast?

The contribution of trends, cycles and seasonality was discussed in detail in the discussion concerning the classical decomposition model. This discussion is under the heading, "Forecasting One Lead-time into the Future." In working with the data, we found that it was difficult to identify a true trend pattern. Rather than trends, the data exhibited random patterns of spiking. Attempts to use a trend component to forecast led to large forecasting errors. A trend line was computed over this data but the line simply accommodated factors from each demand period rather than identifying a real trend pattern. Cycles could only be produced from judgmental factors. If real cycles exist, they are caused by multiple and complex factors that could not be readily identified and quantified for application in a forecasting model. Seasonal factors could be computed and were different for each NSN. The seasonal factors would not be a major enhancement in CLSSA forecasting due to the forecasting horizon crossing multiple years. In summary, trend, cycle and seasonal factors either could not be used or did not improve the accuracy of CLSSA forecasts.

3. What degree of improvement, if any, is achieved by each of the four forecasting methods over the current method?

Although the accuracy exhibited by the adaptive filtering and decomposition models were extremely accurate in following the data and predicting future requirements one quarter into the future, beyond this threshold their performance went to negative forecasting values. These models attempted to force a cyclical, seasonality, and trend to the data. Analysis indicated that the data definitely did not contain identifiable seasonality or cyclical patterns. The double exponential model also fell short in its ability to predict demands for all of the NSNs in the high and medium demand patterns. The double exponential, even with zero values for the seven NSNs it could not predict, predicted 17.1 percent ($452,939) more dollars and 26.3 percent (309) more items than the current method. The only model that could be compared on a one for one basis with the current method was the AFSAC retention model. The AFSAC retention model predicted 9.2 percent ($243,965) more dollars worth of items, however, it predicted 6 percent (70) less items. See Appendix D for the specific details.

4. What degree of improvement, if any, is achieved by the three traditional forecasting methods over the proposed AFSAC forecasting method?

Based upon the various forecasting method characteristics identified during the literature review, we initially selected to measure the accuracy of the double exponential smoothing, adaptive response, and classical decomposition methods in relation to the accuracy of the AFSAC retention formula. As previously discussed, both the adaptive response method and the classical decomposition method were eliminated from consideration early in the research process. Only the double exponential method remained from the original group of traditional methods.

For the 24 month forecast, the AFSAC retention formula performed the best of all methods tested when forecasting for the combined H and N-coded demands. However, this measure is not directly relevant to the planned forecasting implementation of the new

CLSSA process. The new CLSSA process will separately compute an H-coded forecast and a N-coded forecast for each NSN and then combine them to establish the CLSSA stocklevel for the NSN. Therefore, in practical terms, the N-coded only 24 month forecast is of greater interest. In this forecast, the AFSAC retention formula produced a 4.5 percent more accurate forecast than the double exponential method. However, the four period moving average produced an 18 percent lower MSE than the AFSAC retention formula. After the large error attributable to 5 of the 64 NSNs was removed, the AFSAC formula produced the lowest MSE which was 33 percent better than the double exponential smoothing method and 12 percent better than the four period moving average.

For the 36 month forecasts, the double exponential smoothing method produced more accurate forecasts than did the AFSAC retention formula. Double exponential smoothing generated an MSE that was 21 percent lower for the combined H and N-coded category and was 37 percent lower for the N-coded only category. The four period moving average was the best performer in both of these demand categories. Compared to the AFSAC retention formula, the four period moving average produced a MSE 31.6 percent lower for the combined H and N-coded category and 49 percent lower for the N-coded only category than the AFSAC retention formula.

When the error from 5 of the 64 NSNs was removed from the computation, the AFSAC retention formula was again the best in both categories (combined and N-coded only) with an MSE 9 percent and 44 percent better than double exponential smoothing. The AFSAC method was also 11 percent and 38 percent better than the four period moving average in both categories.

For the 9 month H-coded only forecasts, the double exponential smoothing method produced a MSE 30 percent lower than the AFSAC retention formula. When the error caused by 5 of the 64 NSNs was removed from the computation, the difference between double exponential smoothing and the AFSAC retention formula was even

greater. With the revised MSE, double exponential smoothing produced a 72 percent lower MSE than did AFSAC's retention formula. Excluding the error from the 5 NSNs greatly reduced the MSE for double exponential smoothing but resulted in just a limited MSE reduction for the AFSAC retention formula. The best 9 month performer was the four period moving average which produced a 54 percent lower MSE than AFSAC's retention formula when forecasting for all 64 NSNs and generated a 79 percent lower MSE when forecasting with the 5 high error NSNs removed.

5. In general, will forecasting based on historical demands result in higher or lower quantities of CLSSA reparable requirements compared to the current method?

In general, the forecasting models all performed about the same with minor differences in the quantities predicted. Each model's performance improved as the data patterns matched each model's characteristic. The AFSAC model overall seemed to perform the best over the data patterns tested with the lowest MSE value. However, the double exponential would not compute for item M22, because it could not find the optimal alpha value.

Comparing the model with the highest MSE (double exponential) and the lowest MSE (AFSAC) with the current method resulted in an overall increase in the quantity of items required to be included on the FMSO I case. However, when compared to the actual demands received, the current method's prediction was 30 items short of the requirement in the high demand category, and 367 items over the requirement in the medium and low demand categories. The current method over predicted 223 items in the medium category and 144 items in the low category. Thus, the current method's forecast was off by 397 items when evaluated against the customer's actual requirement. These comparison are presented in Appendix E.

The AFSAC model's performance, when compared to actual demands, over predicted the requirement in the high and medium demand categories and significantly under predicted the requirement in the low demand category. The amount of the over prediction was 234 items in the high category, and 43 items in the medium category. The under prediction equated to 20 items in the low category. Overall, the performance of the AFSAC model, when compared to actual demands, resulted in a difference of 297 items.

As evidenced by the data, the AFSAC method performed better than the current method because it predicted 100 less incorrect items. However, if the AFSAC model is adjusted to round down for items with a forecasted value of less than one, the performance of the AFSAC model is improved by 5.3 percent or 16 items. The total number of incorrect items is reduced from 297 items to 281 items over the requirement. Thus, the AFSAC model tends to be a better choice in predicting the correct items to be placed on the stocklevel case than the current method.

6. In general, will the amount of investment funds need to increase to support the quarterly CLSSA reparable requirements predicted by the forecasting method?

Because a direct relationship could not be established about the accuracy of a forecasting method based on the cost of the items forecast, the data was evaluated using three different methods. The first method was to calculate an average cost for all items within the sample for use in comparing the models. This was calculated by taking the total cost ($13,189,090) of the sample divided by the total quantity of 4,722 demands to arrive at an average value per item of $2,793. This average value was then assessed to the total quantity difference among the models. As identified in the Table 14, the lowest dollar value for the FMSO I case would be achieved if the actual requirements could be predicted with 100 percent accuracy. The next best model in both dollar value and quantity was the Air Force Security Assistance Center Rounding Down (AFSACD)

model where the forecasted values are rounded to zero for values less than one, followed by the Air Force Security Assistance Center Rounding Up (AFSACU) model, where forecasted values less than one are rounded upwards to one. The current method resulted in a value that was $941,241 higher than the actual demand. If this is a representative sample of the population, and this error relates to only 1.27 percent of the population (136/10,696 NSNs), then by extrapolation the amount of error in the total population of FMSO I items would equate to $74,113,465 worth of items being held in the absence of a demand. As expected, from its higher MSE value, the double exponential was the worst performer predicting $1,804,278 worth of additional requirements above actual demands. However, these results are based on taking the quantity predicted by the model and multiplying them by the average unit price of $2,793, and should not by themselves be used for evaluation purposes.

TABLE 14

Average Value Analysis One

Model	Avg Value	Qty
Actual	$2,343,327	839
Double	$4,147,605	1485
Current	$3,284,568	1176
AFSACD	$3,044,370	1090
AFSACU	$3,089,058	1106

The second analysis conducted was to calculate and average cost within each category to determine if the model performs better based on certain demand patterns. Using this criteria the model that performs best in the low category is the AFSACU model because it comes closest to predicting the actual quantity demanded by only 10 items, Table 15. Since the multiplier, $1,462 (average unit price per category of items) evaluation can easily be accomplished using the quantity differential by itself. However,

when comparing overall model performance, the significance of the different multipliers will become evident.

A significant point to recognize in the low demand category is that the current method predicts a value 400 percent over the actual requirement. Again if a relationship between items and cost existed, extrapolating this error amount into the total population would equate to $64,320,854 worth of incorrect items being held on the FMSO I case. In the medium category the best performer was the AFSACD model, followed closely (within 6 items) by the AFSACU model. The difference between actual demand and AFSACD model is approximately 20 percent or $82,907, whereas the difference between the actual demand and the current method is 220 percent or $499,679. In the high category, the current method is the better performer in terms of predicting the number of items closest to the actual demand. The current method is only off by 30 items, however, it is off in the negative sense by not predicting enough items. The current method was the clear winner in this category of items because, we submit that it is better to be under by 30 items or $89,280 than to be over by 234 items or $696,384.

In an overall performance rating between the AFSACD model and the current method, based on dollars alone, the likely choice would be to stay with the current method. However, an evaluation based on the total number of items correlated to the actual requirement would lead to implementation of the AFSACD model. This difference is a direct result of the average value of an item in the high demand category being large enough to offset the large 220 and 400 percent errors experienced in the medium and low categories. Thus the value of individual items that reside in each category has a direct impact on the decision of which model is the best performer. It is for this very reason that model accuracy was based on the actual amount of deviation the predicted value was from the actual demand or that the lowest MSE value was chosen as the overall measure of model performance.

TABLE 15

Average Value By Category, Analysis Two

Model	Total Avg Value	Total Qty	High Value	High Qty	Medium Value	Medium Qty	Low Value	Low Qty
Actual	$2,287,410	839	$1,800,479	605	$416,772	186	$70,158	48
Double	$3,793,508	1485	$2,874,815	1052	$918,692	433	N/A	N/A
Current	$2,908,284	1176	$1,711,199	575	$916,451	409	$280,632	192
AFSACD	$3,037,468	1090	$2,496,863	839	$499,679	223	$40,925	28
AFSACU	$3,065,529	1106	$2,496,863	839	$513,123	229	$55,541	38

A third analysis was conducted by taking the average cost of each NSN requisitioned over the ten year sample period, multiplying it by the actual demand that occurred in the quarter, and then comparing the differences in the NSN demand forecasted by each model. The purpose of this analysis was to simulate the actual operation of the model and to calculate a FMSO I case value based on the actual NSNs and quantities forecasted by each model. The result of this comparison is provided in Table 16. The table shows that there is a disparity not only in the number of items predicted in the medium demand category, but also in the mix of the items that make up the forecast. This is evident by the fact that the actual demand for 223 items costs only $529,286 yet the actual demand for the forecast period was a different mix of 186 items at a cost of $565,389. This scenario is again evident in the total value column where the actual demand for 839 items costs more than the forecasted demand for the current method and the AFSACD model. Based solely on the total dollar value column the best method is the current method followed by the AFSACD method. The double exponential model was excluded because values for the low demand items were not calculated. Again making an evaluation solely on the results of the total items or total cost of the model is not recommended because this summary chart does not give a sense of the number of times each model's forecast differed, along with its magnitude, from the actual demand experienced. This table shows that if the models perform as depicted in the sample then the model with the lowest FMSO I value would be achieved using the current method,

followed by the AFSACD model. However, experience has shown that the current method does not contain the right mix of items. Therefore, it is a question of whether or not it is worth the additional $195,828 in an attempt to predict the right items.

TABLE 16

Actual NSN Price Comparison, Analysis Three

Model	Total Value	Total Qty	High Value	High Qty	Medium Value	Medium Qty	Low Value	Low Qty
Actual	$2,987,815	839	$2,217,039	605	$565,389	186	$205,387	48
Double	$3,101,748	1485	$2,410,314	1052	$691,434	433	N/A	N/A
Current	$2,648,809	1176	$1,681,375	575	$638,934	409	$328,500	192
AFSACD	$2,844,637	1090	$2,233,643	839	$529,286	223	$81,708	28
AFSACU	$2,892,774	1106	$2,233,643	839	$548,442	229	$110,689	38

Using the most general analysis, analysis one, we expect the value of the FMSO I case to decrease as the significantly large number of low or no demand items are removed from the case and replaced with items that have an active demand. Since forecasting methods were only concerned with the accuracy of the forecast without regard to the price of the item, we should be able to infer that less items are cheaper. Therefore, even though it seems that the AFSACD or AFSACU model will over predict the actual demand, it should over predict by a lesser amount than the current method. And since items equate to dollars, regardless of the price of the item predicted, less items predicted should mean less dollars required for improved support.

Demand Analysis

An additional criteria used in evaluating forecasting models for the AFSAC was the analysis of the demands, Table 17. An analysis of the demands and the percent of dollar values in each category indicates that AFSAC should select a model that performs best in the high and medium categories because 85 percent of the items and 98 percent of

the dollars are in the high and medium demand category. And since AFSAC is in the business of selling support, a model that excels in the high demand category, the profit generators would be more advantageous to AFSAC than a model that concentrates on the low or medium demand category. In the research, both the four period moving average and the AFSAC retention performed reasonably well in the high demand category. This demand analysis also substantiates the need for AFSAC to fine tune its model to round down for items with a forecasted demand less than one. Adjusting the AFSAC retention formula to round down would eliminate some of the wasted management effort in trying to control the plethora of low demand items which equate to only 2 percent of the dollars.

TABLE 17

Percent of Dollars and NSNs by Category

Number of Demands	Dollar Value	Percent Dollars	NSNs per Category	Percent of Total NSNs
1 to 2	$283,836.35	2%	35	35%
3 to 32	$2,635,079.20	20%	51	52%
33 to 210	$10,270,174.64	78%	13	13%
Totals	$13,189,090.19	100%	99	100%

Summary of Results

Accuracy Comparison - The range of forecast error as represented by the difference between the 'best' and the 'worst' forecast for each method is not great in terms of actual items. The overall range of error between the 'best' and 'worst' methods tested averaged +/-5.8 items. With the large error values attributable to 5 specific NSNs removed, the range of error dropped to +/- 3 items. These results lead to the conclusion that, as a whole, all of the forecasting models examined against performed with an approximately equal amount of accuracy.

Financial Impacts - In addition to the MSE comparison, dollar value and the number of items predicted by the double exponential and the AFSAC models were compared to actual demands, to historical stocklevel records, and to the stocklevel dollar value as predicted by the current model on fourth quarter 1991. This comparison showed that the AFSAC model predicted a lower dollar value FMSO I investment for the medium and low demand category of items. However, for the high demand items, the current method of letting each country predict their demands required a $785,663.90 lower FMSO I investment ($1,711,199.77 versus $ 2,496,863.67) than did the AFSAC model prediction. Additionally, the current method resulted in a greater range of items on the stocklevel case (839 versus 575, a difference of 264 items) than did the AFSAC model. Considering the cumulative impacts in the low, medium and high demand categories, the AFSAC model required a $157,244.43 greater FMSO I investment, but also resulted in 70 less NSNs being placed on the stocklevel.

Category Relevance - The most relevant categories to compare accuracy are the N-coded 24 and 36 month categories and the 9 month H-coded categories. The reasons these were considered to be the most relevant measurement categories are 1) the new CLSSA program will use separate H-coded and N-coded forecasts to compute stocklevels, therefore, the combined categories are not relevant measures, and 2) high error forecasts cannot simply be excluded from consideration in actual CLSSA operation as was done for this research.

In considering only the relevant demand categories, the four period moving average was the most accurate method in each category. Table 13 presented these results in comparison to the AFSAC retention formula results. Although the margin of improved accuracy is relatively small, the four quarter moving average method surpassed the AFSAC method by an average of +/- 6 items when forecasting for the relevant categories

only. Therefore, of the methods tested, the four period moving average method is the most accurate for actual CLSSA investment item forecasting.

Demand Spiking - Demand spiking was not hypothesized to be a factor influencing CLSSA forecasting. However, demand spiking was a major source of error for all the methods tested. For this reason, separate measurements were made that excluded the five most dramatically impacted NSNs. These five NSNs had demand patterns dominated by large spikes ranging from 500 to 1100 percent of average demand. Although these large errors cannot simply be ignored when actually forecasting for CLSSA, action can be taken to limit their influence on the forecasts. If action is not taken to treat these demand spikes, forecasting models will predict significantly more items to be placed on the stocklevel than average demands actually require. Later in this chapter some recommendations are offered for treating the demand spikes. If the demand spikes can be effectively treated, this research indicates that the AFSAC retention formula would produce the most accurate results for the N-coded items.

AFSAC Retention Formula Weighting Scheme - The AFSAC retention model progressively decreases the weight of older demand values while placing greater value on the most recent values. No benefit was found by weighting demand values based upon chronological age when no trend exists. The only advantage provided by the weighting scheme is that it progressively reduces the influence of atypical demands as they become older. The key element in making accurate forecasts appears to relate to determining the true mean demand over the lead time period. Rather than applying decreasing weights to 16 quarters of historic demand data, the true mean demand could be approximated more accurately by excluding or adjusting atypical quarterly demands so that they do not inappropriately influence the average lead time demand.

Inventory Management Principles - This research indicates that the issue of determining an appropriate CLSSA stocklevel may be better answered using traditional inventory management formulas rather than forecasting methods. This conclusion stems from observing that the 'best' forecast performer in the relevant categories (four period moving average) simply averaged demand over the lead time to develop a forecast stocklevel. The traditional inventory management formulas calculate a stocklevel using the average demand and the standard deviation that occurs over the lead time. In addition, the inventory management approach considers the average lead time and the standard deviation in the lead time. Equipped with this information, managers can subjectively determine the level of support to be provided. The stocklevel is determined by computing the average demand over the lead time and then adding the number of standard deviations of lead time/demand that correspond to the confidence level of support desired. A complete presentation of this approach to stocklevel calculation can be found in most inventory management texts.

V. Conclusions and Recommendations

Conclusions

This research focused on determining if an automated forecasting method based on historical demands could accurately predict future CLSSA investment item demands. Based upon the results obtained from this research, implementation of an automated CLSSA stocklevel forecasting model is warranted. Automated models favor having the right mix of items, but require a higher level of customer investment cost. This is because automated models dynamically respond to customers' actual demand patterns in calculating stocklevels. As a consequence, they predict higher quantities across a narrower range of recurring demand items. The current manual forecast method results in a lower investment cost because it invests in lower quantities across a broader range of items. The mix of materiel forecast by the current manual method includes many items that will not be demanded. An automated model such as the AFSAC retention formula is preferred in spite of the higher customer investment cost because an automated forecasting process better supports the fundamental purpose of CLSSA which is to provide timely recurring logistic support at the most reasonable cost.

Considering just the raw data with its demand spikes, the four period moving average model produced the most accurate forecasts, in each of the relevant demand categories; N-coded only at 24 months, N-coded only at 36 months and H-coded only at 9 months (see Tables 4, 8, and 10). This result indicates that a simple, unweighted moving average forecasting model performs better on CLSSA historical data than does the more sophisticated methods of exponential smoothing or the AFSAC retention formula. However, if demand spikes are controlled, the AFSAC retention formula produced the

most accurate results in the relevant categories except the H-coded only at 9 months (see Table 5, 9, and 11).

Recommendations

The following additional recommendations are considered important to further evaluate the results and to extend the scope of this thesis:

1. Additional research into methods that fine tune the AFSAC model to effectively control the influence of atypical demand patterns (demand spiking). The three choices are: 1) ignore the demand patterns and treat all items alike (essentially do nothing), 2) develop an automated program to catch programmed requisitions with abnormally high demands (exceeding a specified number of standard deviations from the mean) and have them verified prior to acceptance, and 3) treat the high quantity requisition as a valid recurring demand, but then have SAMIS increase the normal stocklevel value by a portion of the spiked demand (increase the average stocklevel value by 2 times the historical normal demand). Without a mechanism to control these data patterns, excessive quantities will be procured. This diverts the limited financial funds from the actual recurring requirements.

2. Further analysis into the performance of the models should be conducted. The sample, although it appeared to reflect the true population, may contain confounds related to the particular NSNs selected, which may have corrupted the results. A different average unit price mix between the high, medium, and low demand categories would change the outcome of the financial analysis comparison. Testing another sample of 136 NSNs is recommended to determine if the results are approximately the same.

3. An analysis should be conducted to define recurring demand in relationship to a specific time frame. The goal of the CLSSA program is to provide support for recurring

demands. Demands that do not meet the definition of recurring should not be supported with a CLSSA stocklevel. Once this is clarified, adjustments to the AFSAC model could be made that would increase the accuracy of the model.

4. If an automated stocklevel forecasting model is not implemented, additional research is required to investigate alternate methods to control the large number of item stock numbers placed on the stocklevel when no demands are ever submitted for those items. Almost 26 percent of the stratified random sample received for this study exhibited zero demand.

Summary

Although the ideal result would be to obtain zero forecasting error, an automated forecasting model with means to treat demand spikes will produce an acceptable level of accuracy. Automated forecasting models permit efficient, reasonably accurate quarterly recalculation of all CLSSA investment item stocklevels. Because the automated models dynamically respond to changes in item demand rates, FMSO I investment funds are constantly reallocated to the items that are actually being demanded. Equally important is the fact that automated models quickly react to items that have no demand or a decreasing demand. For these type items, these models automatically reduce the stocklevel in proportion to the decrease in demand. This action prevents the CLSSA program from procuring materiel that no customer will actually demand in the future. Continuing to carry items on CLSSA that are no longer required is a financial drain for both the CLSSA participant and for the USAF. The CLSSA participant has its 5/17 FMSO I funds invested in the items it does not require when the funds could be better used to buy the items for which demands actually recur. The USAF is negatively impacted because when the material is delivered to the US depot and no CLSSA participant has ordered the items on a FMSO II, the USAF must pay the 12/17 of the materiel value. The USAF has then lost

the use of this 12/17 value for an undetermined period until some CLSSA participant orders the item.

An automated forecasting model also simplifies the CLSSA management process. By eliminating the complex and time consuming manual forecasts processes, CLSSA participants will be able to reallocate their supply resources to other more productive uses. The dynamic nature of the automated forecasting model eliminates the need to conduct the semi-annual CLSSA renegotiations. Additionally, as customer supply personnel turnover, the learning curve related to CLSSA management for new personnel will be greatly shortened.

The most significant result of transitioning to an automated investment item forecasting model will be improved customer satisfaction. CLSSA participants will gain more benefit from their FMSO I investment. With the FMSO I funds being constantly applied to the items that will be actually demanded, materiel should be on the shelf or already on order. As a result, requisition fill-time rates for CLSSA investment items should improve. As CLSSA FMS customers begin to receive improved performance from CLSSA, they may desire to have more of their weapon systems supported via the program. Additionally, as current non-CLSSA FMS customers recognize the improved supply service available under CLSSA, they may be motivated to become participants. CLSSA by definition is a cooperative program. As the number of systems and customers being supported grows, the overall service to each individual member of the cooperative will increase. In other words, a synergism develops as more materiel is procured under CLSSA.

As noted earlier, 97 percent of all requisitions submitted to the AFSAC are on FMSO II cases. Efficient and timely logistic support via the USAF's new approach to CLSSA will be a notable factor as friendly nations of the world consider which source to acquire their next major weapon systems. The US has long maintained a reputation for

reliable and effective systems. If a corresponding strong support record can be created via the new approach to CLSSA, the US as a whole will gain from the political, military and economic benefits derived from additional FMS demand for US weapon systems.

Appendix A: Sample National Stock Numbers

Randomly Selected List of 136 NSNs

1650000043744	4130010398991	5998009190024	6130013100808
6610000458132	6625010400671	5821009290904	5998013292520
2995000884182	6625010405961	2840009366719	1240997360412
6685001159606	6625010405964	6620009898692	6150010993238
6685001213348	2915010415660	6610009898886	6150011013073
5998001225049	6625010429806	6625009957472	4920011023902
2840001227122	5821010441810	5998009958756	6110011043082
5895001368237	5998010492636	5998009970821	6340011047804
1430001444407	5998010543961	7050010033121	6625011086601
1560001641526	5999010575579	5895010052920	5998011113867
2840001662356	6110010602407	5999010072882	4310011139363
1650002230653	6615010633261	4810010074115	5841011158403
6625002378870	7025010645128	1560010085288	1560011201934
5841002491195	6150010651868	1650010101622	1280011260079
5841002523500	2915010668842	4810010108472	1650011297553
6115002560374	5998010687880	5998010110485	4320011316976
5998002767505	5841010689152	7025010112968	5865011448567
4820003131141	5999010704452	5998010122212	6625011464927
1710003412064	5999010718430	6610010174787	5998005357643
5821003464706	5821010759405	5998010270167	5999005396520
2915003524767	5998010771457	6130010323966	6625006054563
6130003617083	6625010776674	1660010365903	1650006136567
5999003653101	5998010779343	6615010387297	3110006185880
5826004040249	2915010783314	6110011464951	6105006608813
6635004314371	5998010785540	2840011469378	1660006970846
1560004335369	5998010804085	5826011626649	2915007062719
1560004636767	6130010848525	6625011664206	5985007596990
1650004910601	6110010860717	7025011681356	6105007914363
1560004987867	4810010898900	2840011768601	1630008473731
6620005049040	5998010902642	1005011909802	6720008508490
5821005051336	5998010944089	2840011926911	2915008715870
6625005286865	1270010993205	5841012090090	6110008732981
5998012639415	3040012458158	5998012217228	1430009183652
2840012965007	6130012481717	5895012314035	1560012355201

Thirty-Seven Removed NSNs

NSN	Reason For Deletion
1560001641526	No Demand in Ten Year
1650006136567	No Demand in Ten Year
2840001227122	No Demand in Ten Year
2840011469378	No Demand in Ten Year
2915003524767	No Demand in Ten Year
2915010668842	No Demand in Ten Year
4320011316976	No Demand in Ten Year
5821010441810	Only Demand was a Drawdown
5895010052920	Only Demand was a Drawdown
5998001225049	No Demand in Ten Year
5998005357643	No Demand in Ten Year
5998009958756	No Demand in Ten Year
5998009970821	No Demand in Ten Year
5998010779343	No Demand in Ten Year
5998010785540	Only Demand was a Drawdown
5998010944089	No Demand in Ten Year
5998011113867	No Demand in Ten Year
5999003653101	No Demand in Ten Year
5999010575579	No Demand in Ten Year
5999010704452	No Demand in Ten Year
5999010718430	No Demand in Ten Year
6110010860717	No Demand in Ten Year
5998013292520	No Demand in Ten Year
6130012481717	No Demand in Ten Year
6130013100808	No Demand in Ten Year
6150010651868	No Demand in Ten Year
6150011013073	No Demand in Ten Year
6625002378870	No Demand in Ten Year
6625006054563	Only Demand was a Drawdown
6625010400671	No Demand in Ten Year
6625010405964	Only Demand was a Drawdown
6625010429806	Only Demand was a Drawdown
6625010776674	No Demand in Ten Year
6625011464927	No Demand in Ten Year
7025010112968	No Demand in Ten Year
7025010645128	No Demand in Ten Year
7025011681356	No Demand in Ten Year

NSNs Deleted, Drawdown Only Demand

NSN	Quantity	Dollar Value	Julian Date	Disposition
58210104418 10	1	964.20	93312	B
58950100529 20	1	4264.20	90353	B
59980107855 40	2	1317.37	92197	B
66250060545 63	1	1481.22	92204	B
66250104298 06	1	2414.68	93007	B
66250107766 74	1	4052.66	86058	A

		High Demands			
NSN	Total Qty	Total Value	Average Value	Demands	Category
1660010365903	148	1958096.76	13230.38	113	H1
6615010387297	80	388624.18	4857.80	69	H2
2995000884182	846	2467873.20	2917.11	197	H3
1270010993205	206	476267.36	2311.98	172	H4
6340011047804	87	186276.58	2141.11	44	H5
1430001444407	231	92063.96	398.55	58	H6
1560012355201	248	1176737.36	4744.91	116	H7
5841002523500	70	1130757.02	16153.67	48	H8
1650004910601	374	394743.27	1055.46	96	H9
3110006185880	533	73725.77	138.32	92	H10
1660006970846	109	139023.88	1275.45	42	H11
2915007062719	358	1623515.71	4534.96	210	H12
6610009898886	161	162469.59	1009.13	105	H13
Totals	3451	10270174.64	2976.00	1362	

		Medium Demands			
NSN	Total Qty	Total Value	Average Value	Demands	Category
7050010033121	4	2698.12	674.53	4	M1
1650000043744	31	119190.77	3844.86	13	M2
1650010101622	17	32376.52	1904.50	15	M3
4810010108472	16	42038.41	2627.40	15	M4
6610010174787	9	61353.39	6817.04	4	M5
5998010270167	20	10798.63	539.93	13	M6
6130010323966	3	1146.12	382.04	3	M7
4130010398991	12	42248.76	3520.73	11	M8
2915010415660	7	18381.08	2625.87	4	M9
6610000458132	36	25063.29	696.20	13	M10
6110010602407	4	14894.66	3723.67	4	M11
6615010633261	7	9601.56	1371.65	6	M12
5841010689152	4	3397.56	849.39	3	M13
5821010759405	5	6274.96	1254.99	3	M14
5998010804085	8	2629.04	328.63	4	M15
6130010848525	5	25657.38	5131.48	3	M16
4810010898900	38	48772.52	1283.49	29	M17
6625011086601	7	7161.57	1023.08	6	M18
6685001159606	63	54042.75	857.82	24	M19
6685001213348	37	20561.27	555.71	8	M20
1280011260079	3	13918.66	4639.55	3	M21
1650011297553	55	162369.05	2952.16	34	M22
5895001368237	5	6925.46	1385.09	5	M23
5865011448567	19	194396.90	10231.42	13	M24
5826011626649	16	24474.88	1529.68	6	M25
6625011664206	4	5018.84	1254.71	3	M26
2840011768601	12	103390.72	8615.89	3	M27
1005011909802	10	25678.91	2567.89	8	M28

2840011926911	5	75760.87	15152.17	3	M29
5841012090090	7	2098.13	2998.16	6	M30
5998012217228	11	56952.75	5177.52	4	M31
1650002230653	14	17420.46	1244.32	7	M32
5841002491195	10	27904.20	2790.42	6	M33
5998002767505	7	4904.41	700.63	6	M34
2840012965007	3	14136.89	4712.30	3	M35
4820003131141	3	676.55	225.52	3	M36
1710003412064	9	45808.33	5089.81	5	M37
5821003464706	33	1743.14	52.82	4	M38
1560004335369	4	28223.05	7055.76	3	M39
1560004636767	7	142230.42	20318.63	6	M40
5821005051336	6	1188.00	198.00	3	M41
5999005396520	5	56616.63	11323.33	4	M42
6105006608813	114	168549.44	1478.50	29	M43
5985007596990	11	159650.18	14513.65	11	M44
6105007914363	73	46444.12	636.22	28	M45
1630008473731	158	383232.06	2425.52	30	M46
6110008732981	10	7366.36	736.64	4	M47
1430009183652	36	204318.29	5675.51	21	M48
5998009190024	12	53511.10	4459.26	12	M49
2840009366719	167	17753.96	106.31	5	M50
6620009898692	14	34128.08	2437.72	3	M51
Totals	1176	2635079.20	2240.71	466	
		Low Demands			
NSN	Total Qty	Total Value	Average Value	Demands	Category
5999010072882	2	4296.29	2148.15	2	L35
4810010074115	1	7597.28	7597.28	1	L34
1560010085288	1	10869.95	10869.95	1	L33
5998010110485	4	5174.40	1293.60	2	L32
5998010122212	4	4563.04	1140.76	2	L31
6625010405961	1	2559.99	2559.99	1	L30
5998010492636	1	241.92	241.92	1	L29
5998010543961	3	5869.28	1956.43	2	L28
5998010687880	1	1387.37	1387.37	1	L27
5998010771457	1	2492.00	2492.00	1	L26
2915010783314	2	5557.20	2778.60	1	L25
5998010902642	3	7012.52	2337.51	2	L24
6150010993238	5	8250.00	1650.00	1	L23
4920011023902	2	13295.30	6647.65	2	L22
6110011043082	2	41240.80	20620.40	2	L21
4310011139363	1	964.21	964.21	1	L20
5841011158403	5	33797.50	6759.50	1	L19
1560011201934	2	16235.05	8117.53	2	L18
6110011464951	1	1828.48	1828.48	1	L17
2840001662356	21	1075.41	51.21	1	L16

5895012314035	1	15700.00	15700.00	1	L15
3040012458158	5	16876.01	3375.20	2	L14
6115002560374	2	2069.63	1034.82	2	L13
5998012639415	1	2176.28	2176.28	1	L12
6130003617083	2	413.78	206.89	1	L11
5826004040249	3	819.12	273.04	1	L10
6635004314371	2	1700.60	850.30	2	L9
1560004987867	2	3300.00	1650.00	1	L8
6720008508490	2	1461.58	730.79	1	L7
6620005049040	4	2220.68	555.17	1	L6
6625005286865	1	1186.62	1186.62	1	L5
1240997360412	2	33840.44	16920.22	1	L4
2915008715870	2	6441.20	3220.60	2	L3
5821009290904	1	637.36	637.36	1	L2
6625009957472	2	20685.06	6895.02	2	L1
Totals	95	283836.35	1461.63	48	

Appendix B: Data Patterns

High Category Demand Patterns:

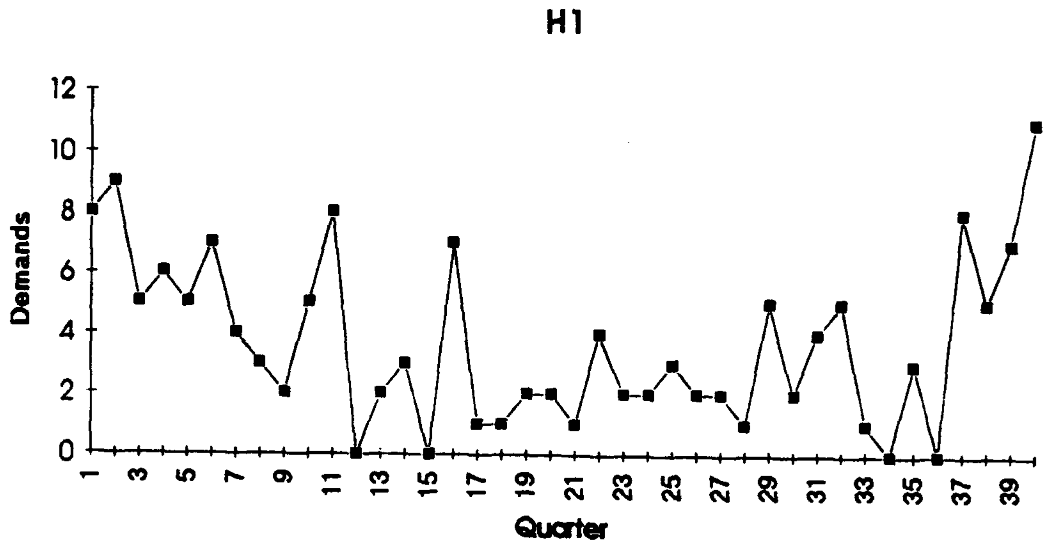

Figure 3. Demand Pattern for Item H1

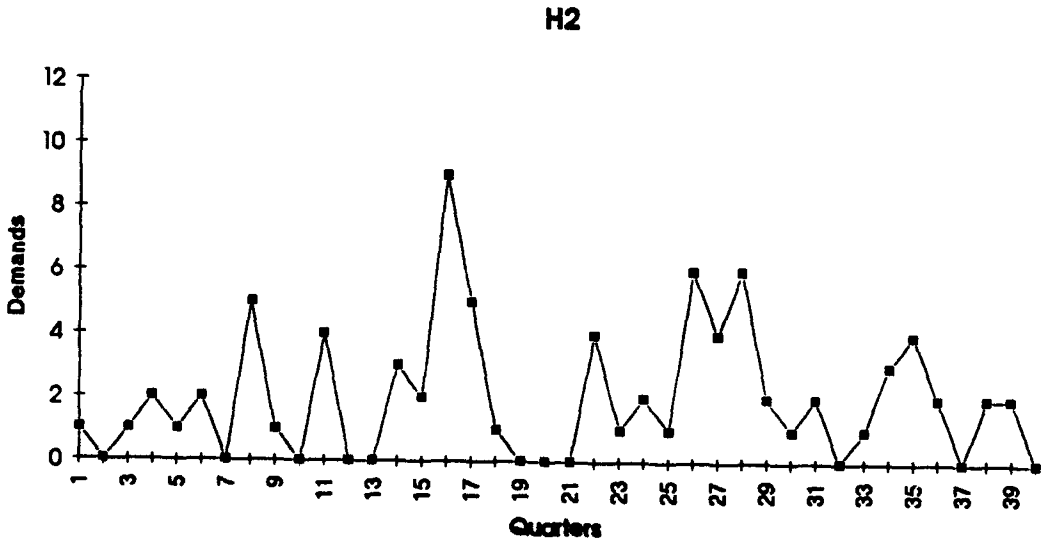

Figure 4. Demand Pattern for Item H2

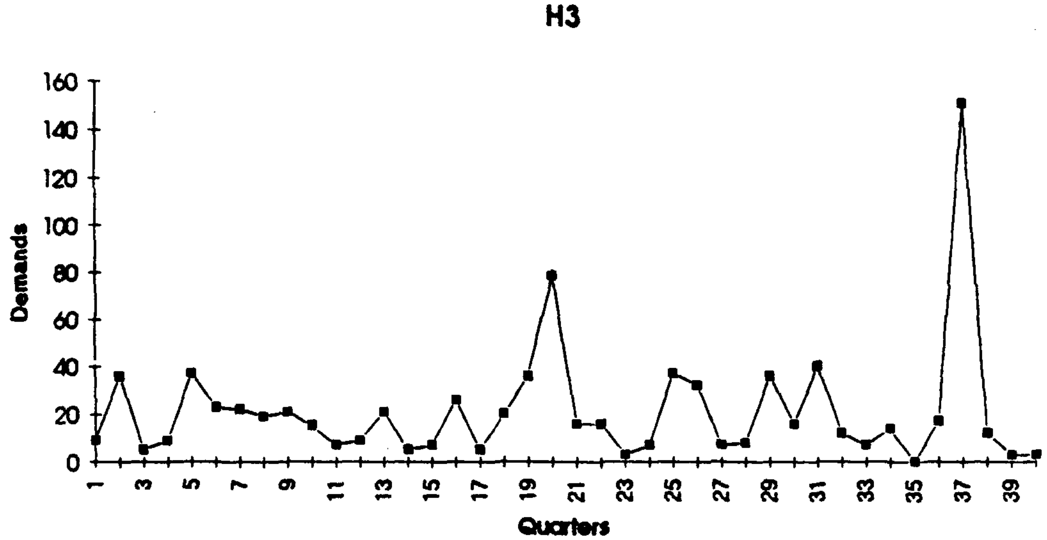

Figure 5. Demand Pattern for Item H3

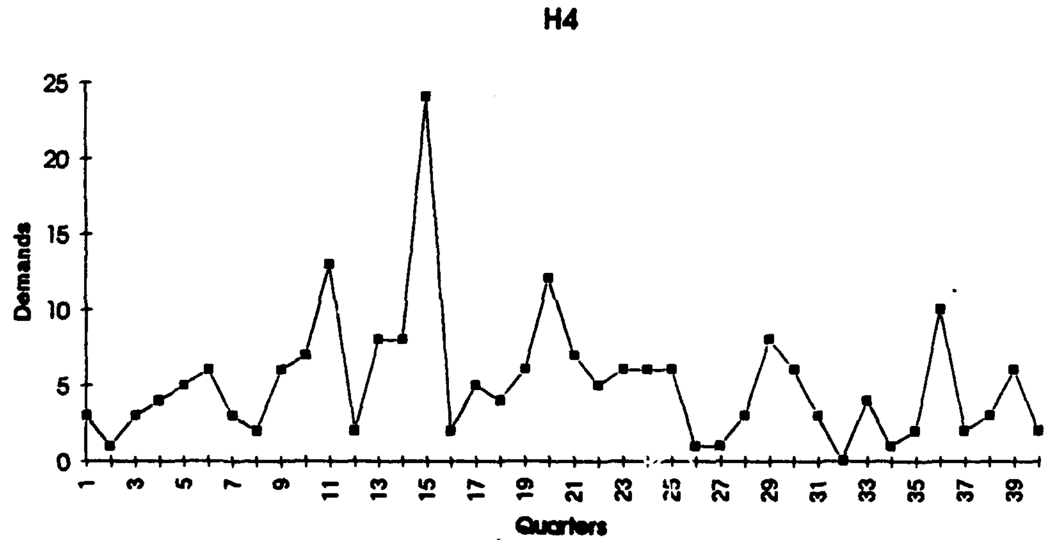

Figure 6. Demand Pattern for Item H4

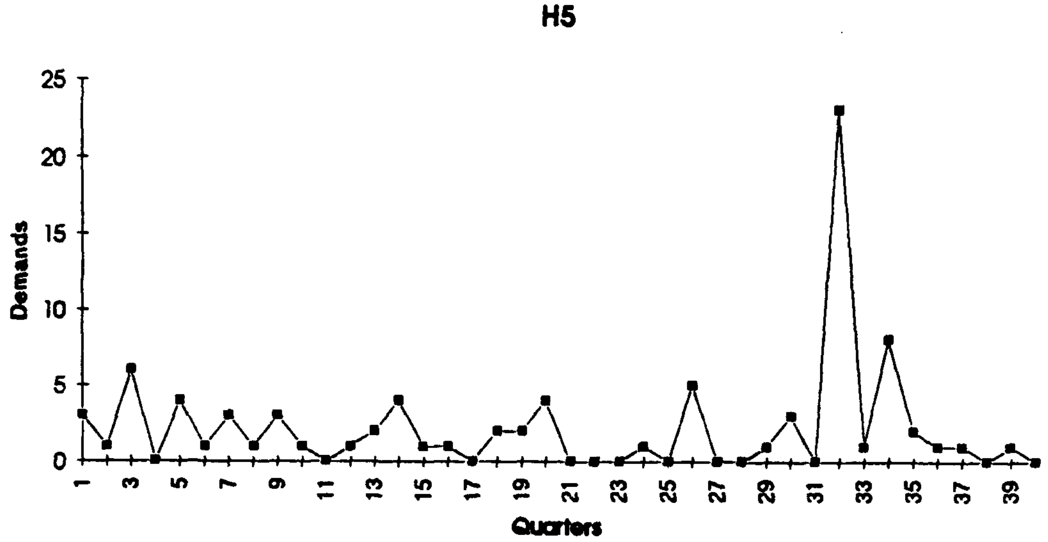

Figure 7. Demand Pattern for Item H5

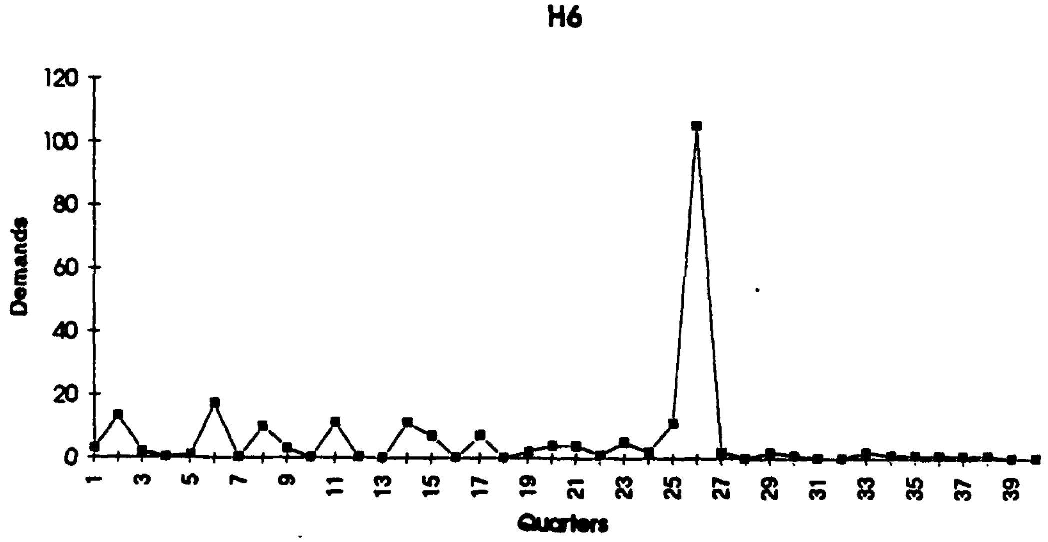

Figure 8. Demand Pattern for Item H6

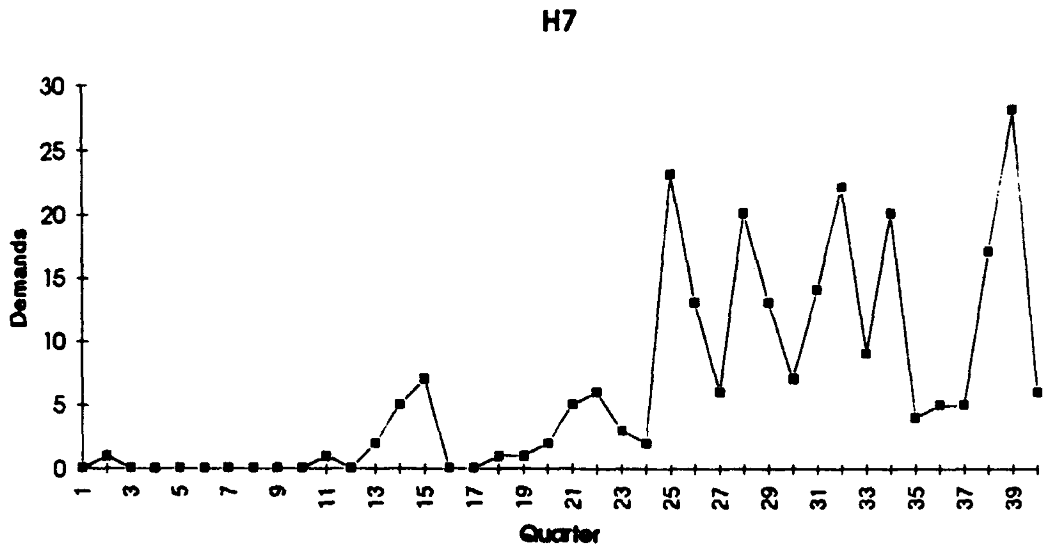

Figure 9. Demand Pattern for Item H7

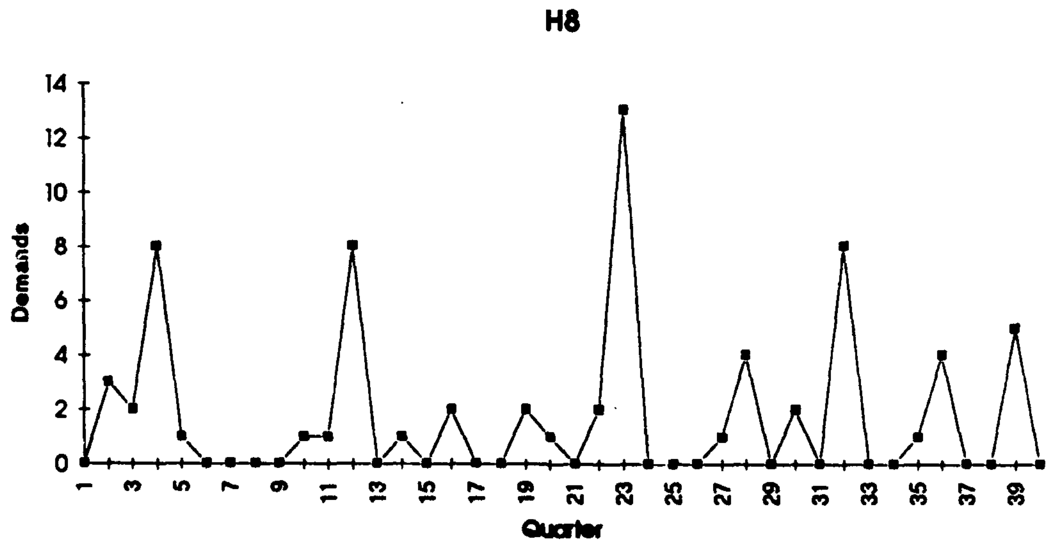

Figure 10. Demand Pattern for Item H8

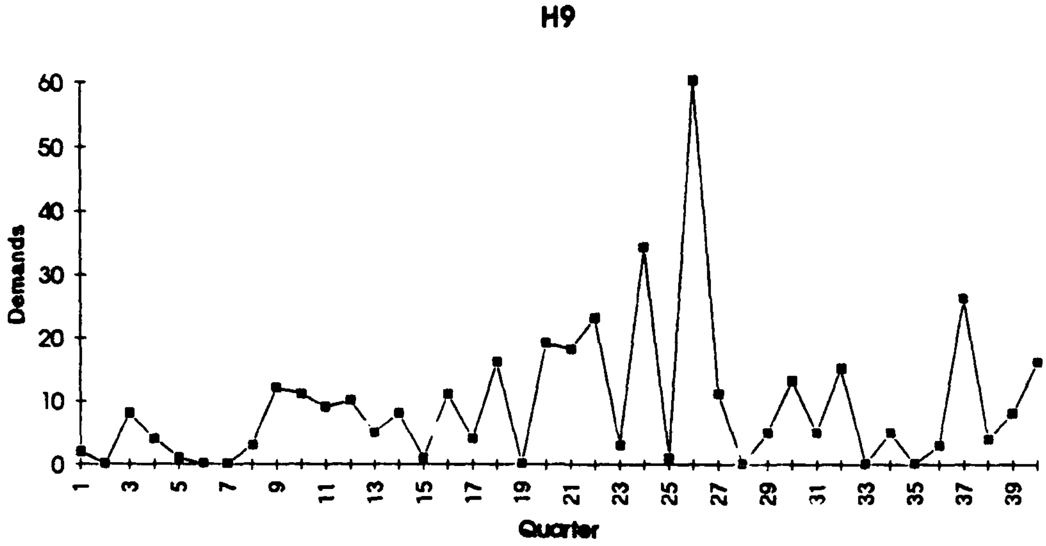

Figure 11. Demand Pattern for Item H9

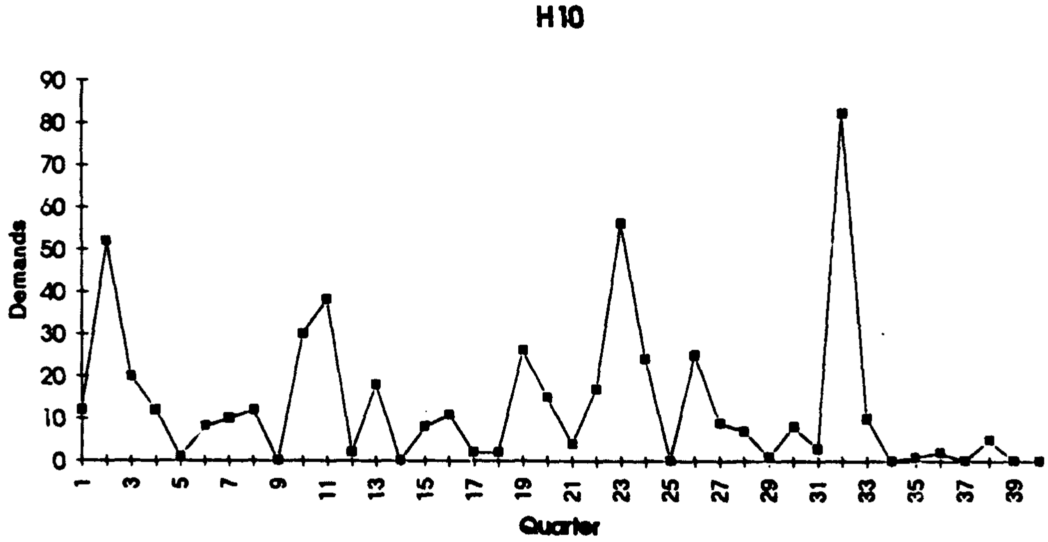

Figure 12. Demand Pattern for Item H10

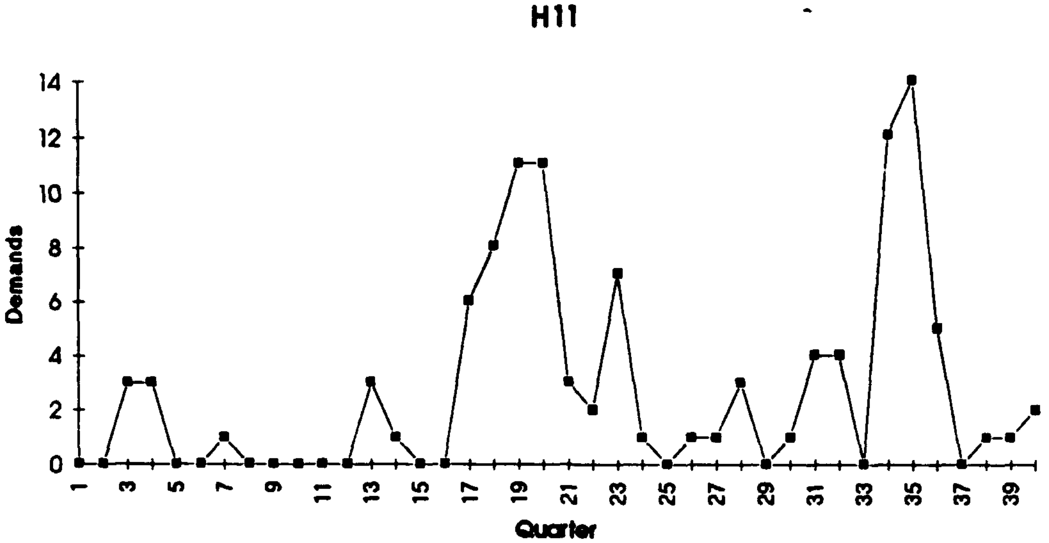

Figure 13. Demand Patter for Item H11

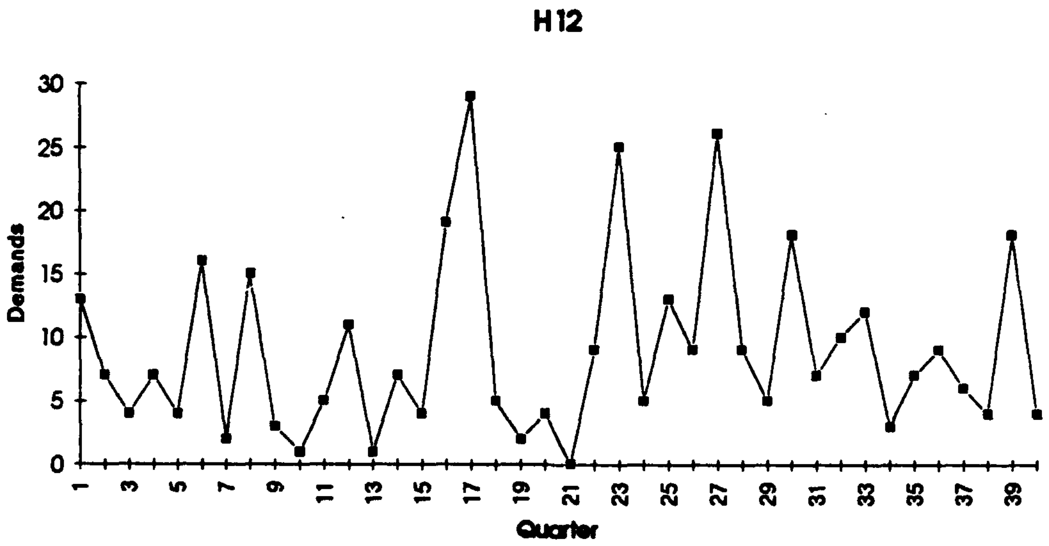

Figure 14. Demand Pattern for Item H12

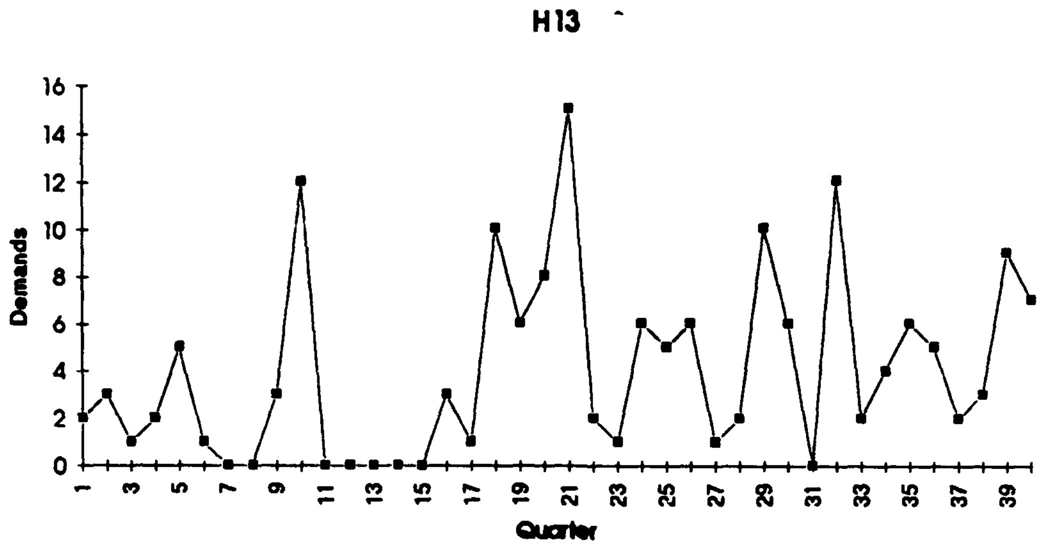

Figure 15. Demand Pattern for Item H13

Medium Combined Demand Patterns:

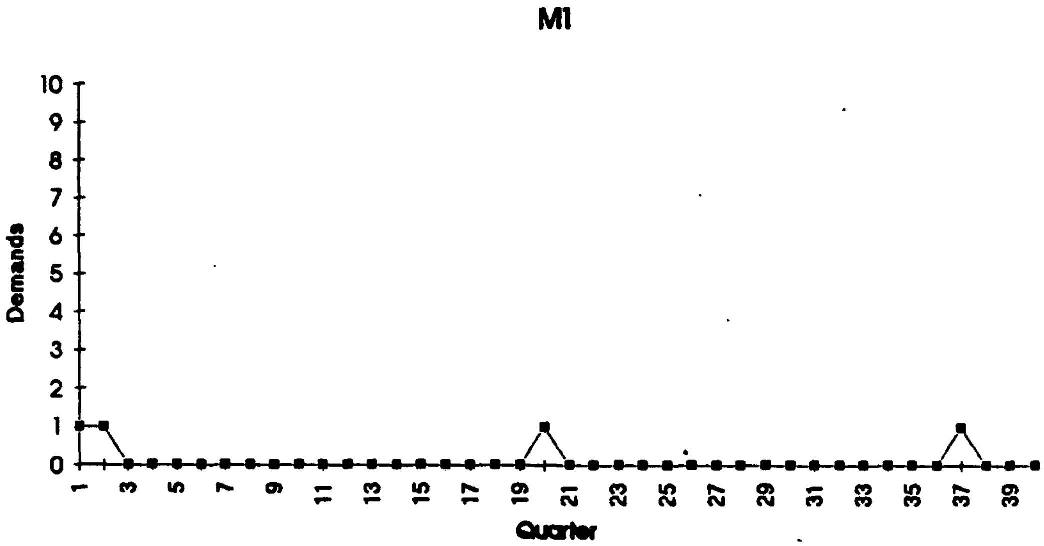

Figure 16. Demand Pattern for Item M1

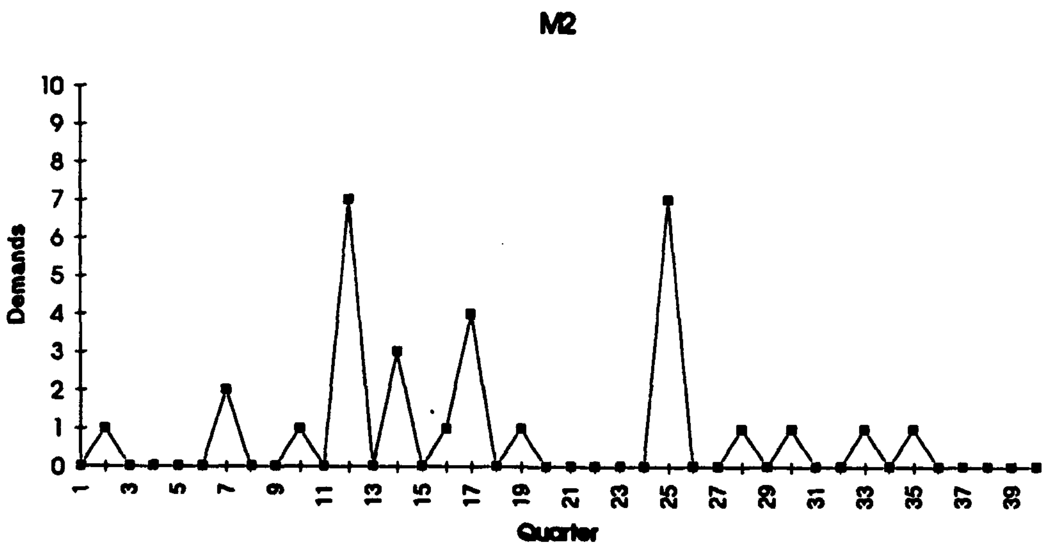

Figure 17. Demand Pattern for Item M2

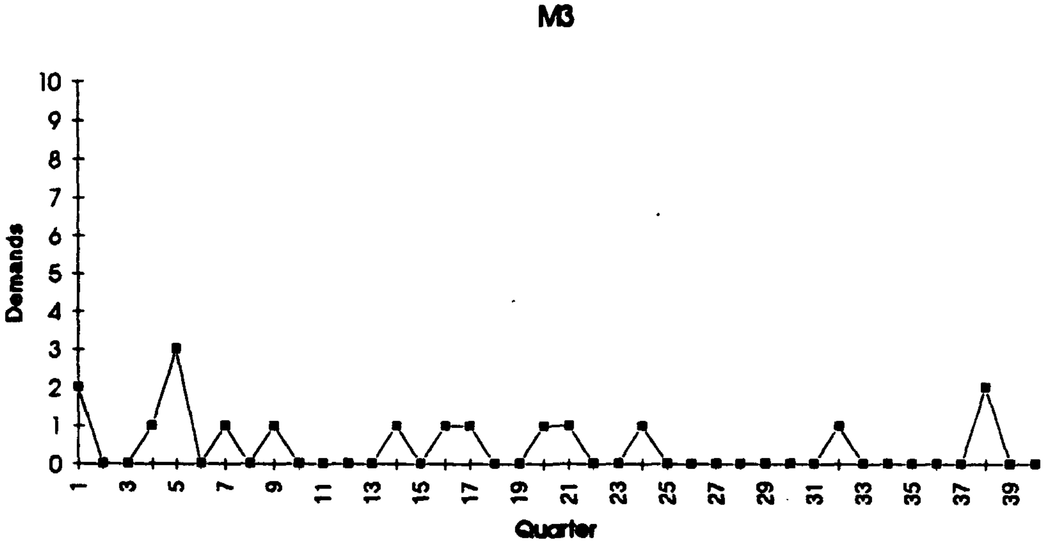

Figure 18. Demand Pattern for Item M3

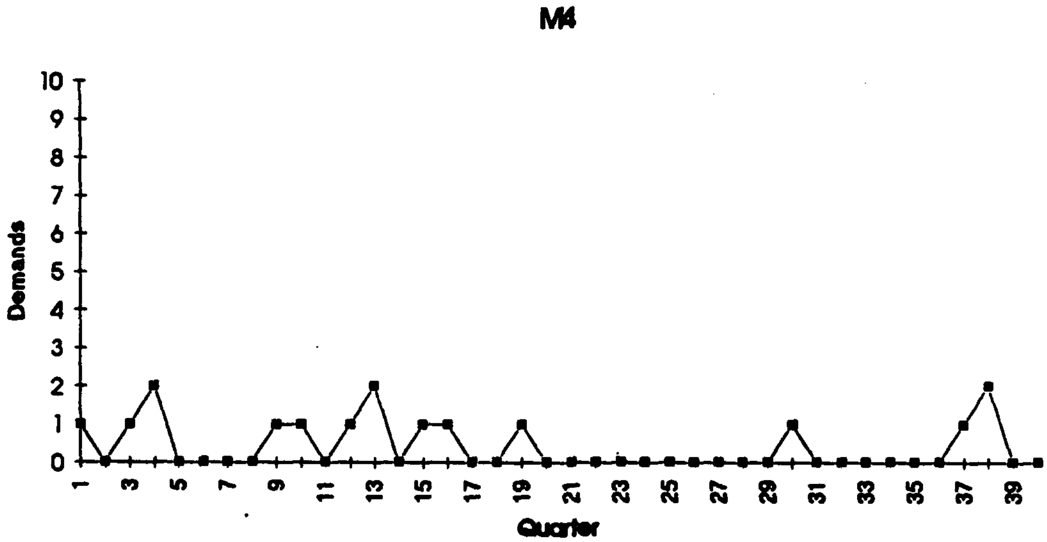

Figure 19. Demand Pattern for Item M4

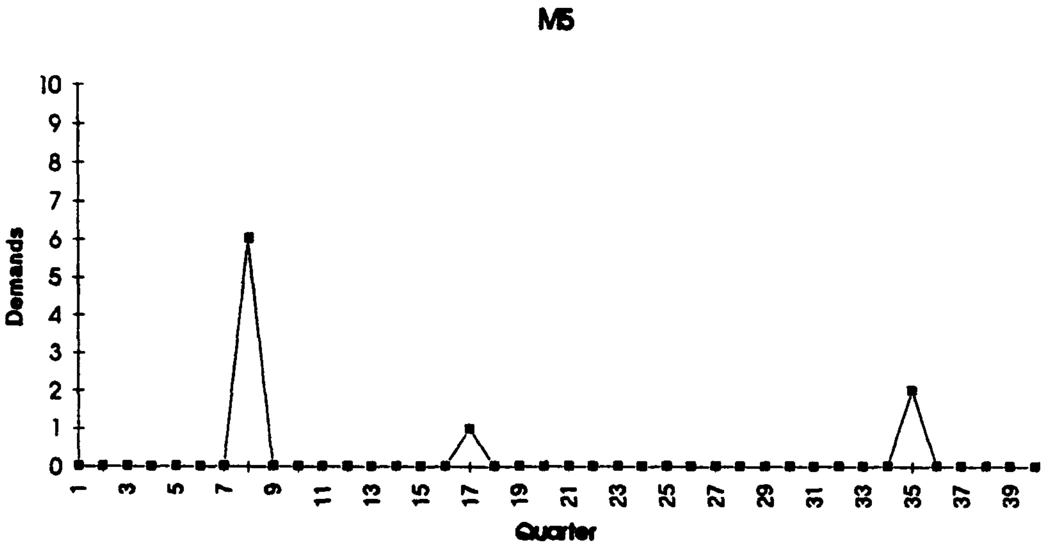

Figure 20. Demand Pattern for Item M5

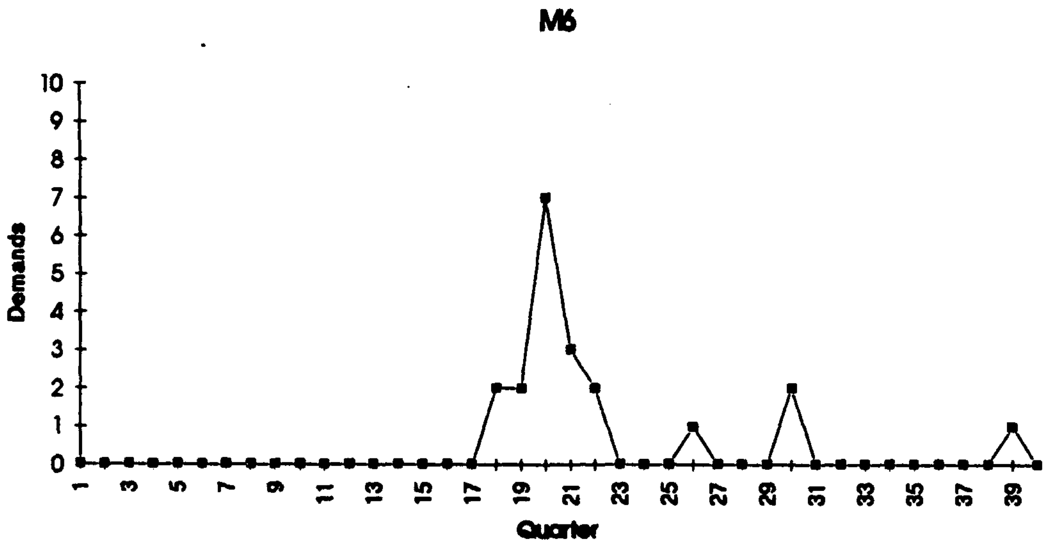

Figure 21. Demand Pattern for Item M6

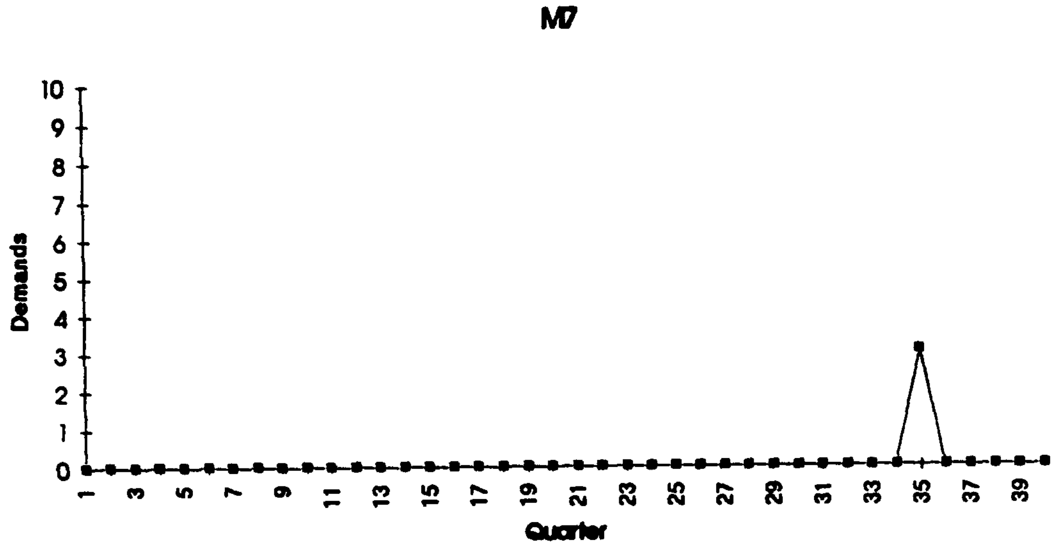

Figure 22. Demand Pattern for Item M7

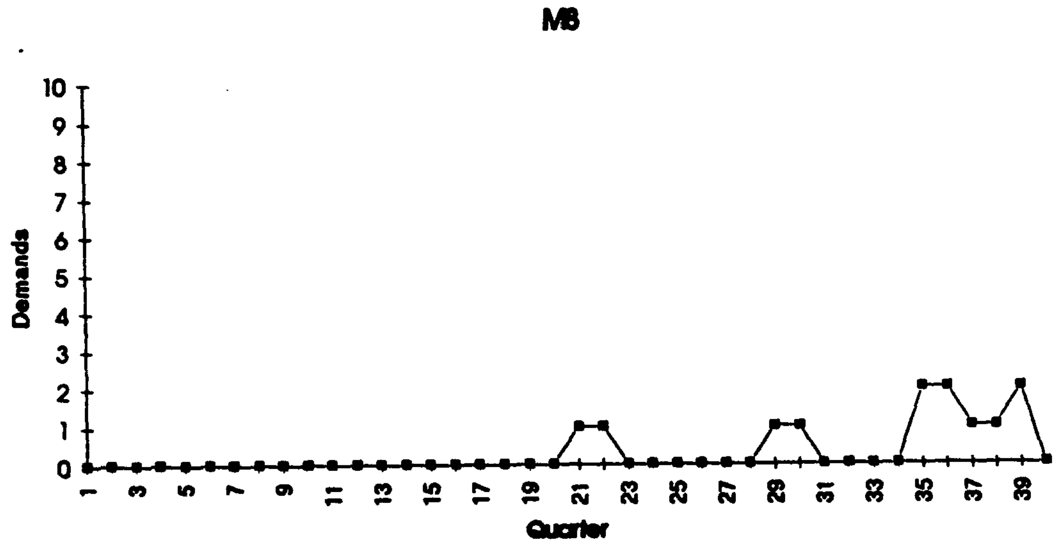

Figure 23. Demand Pattern for Item M8

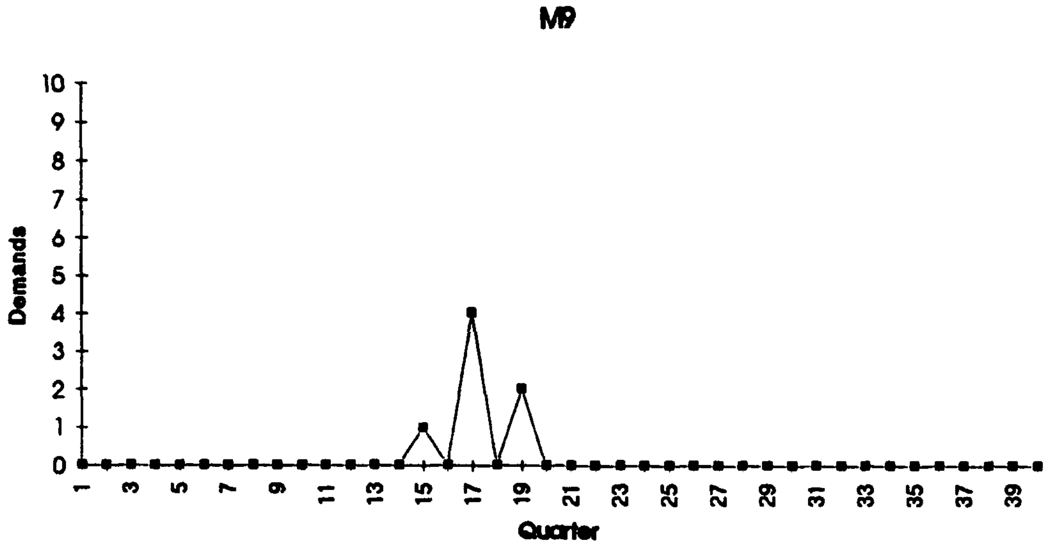

Figure 24. Demand Pattern for Item M9

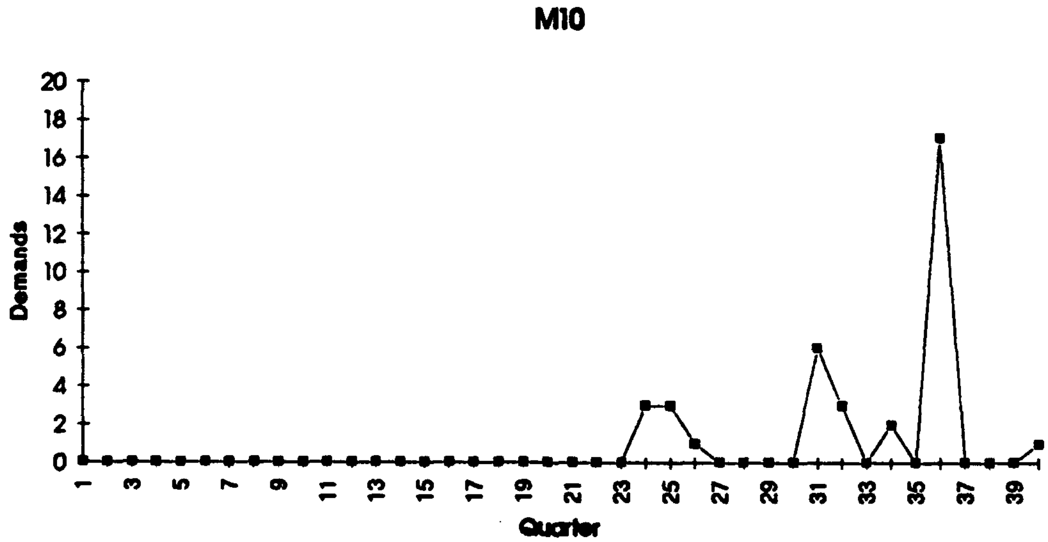

Figure 25. Demand Pattern for Item M10

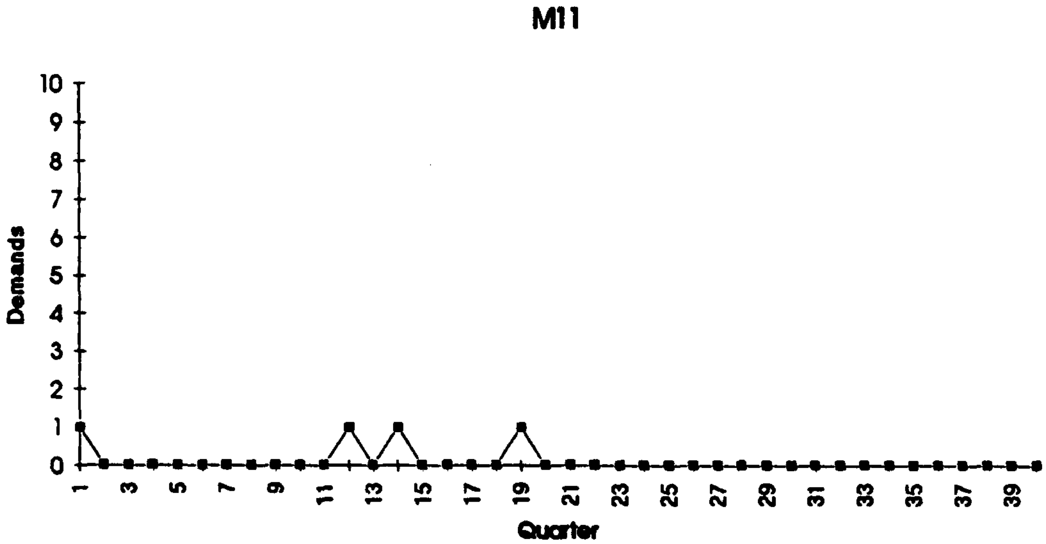

Figure 26. Demand Patter for Item M11

Figure 27. Demand Patterns for Item M12

M13

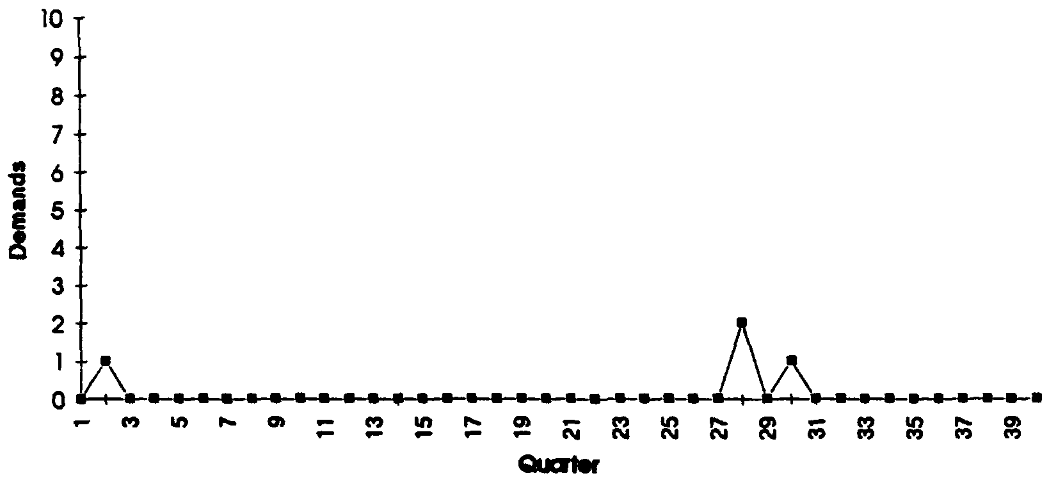

Figure 28. Demand Patterns for Item M13

M14

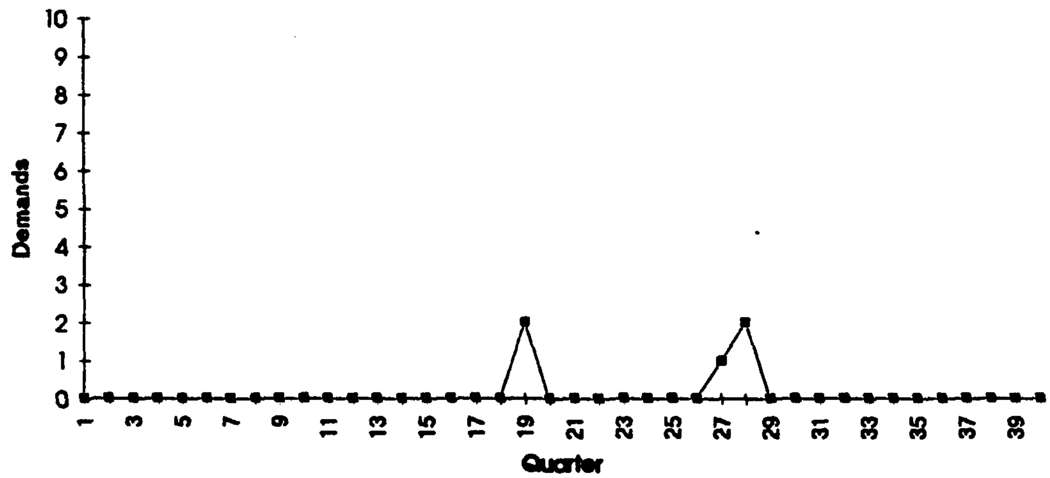

Figure 29. Demand Patterns for Item M14

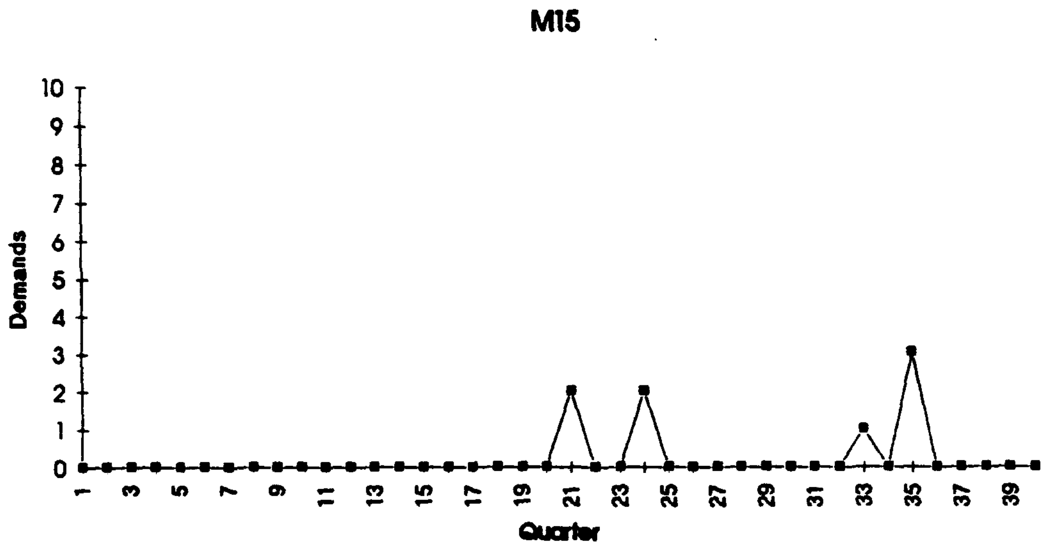

Figure 30. Demand Patterns for Item M15

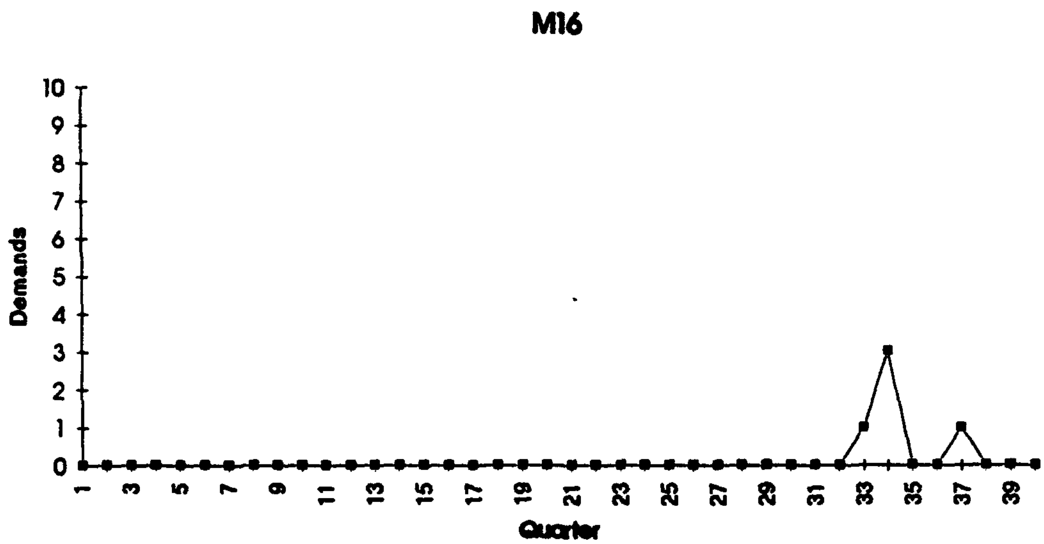

Figure 31. Demand Patterns for Item M16

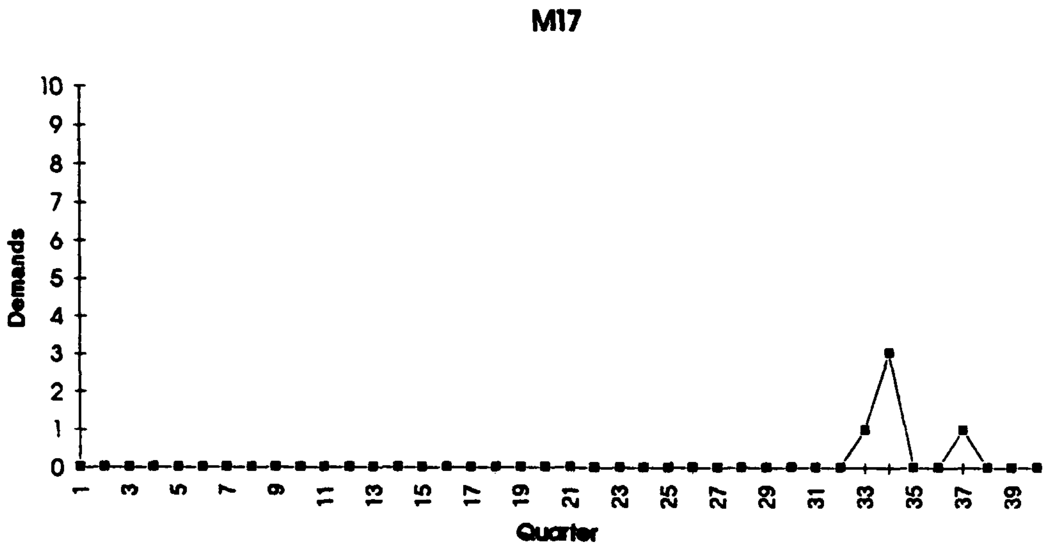

Figure 32. Demand Patterns for Item M17

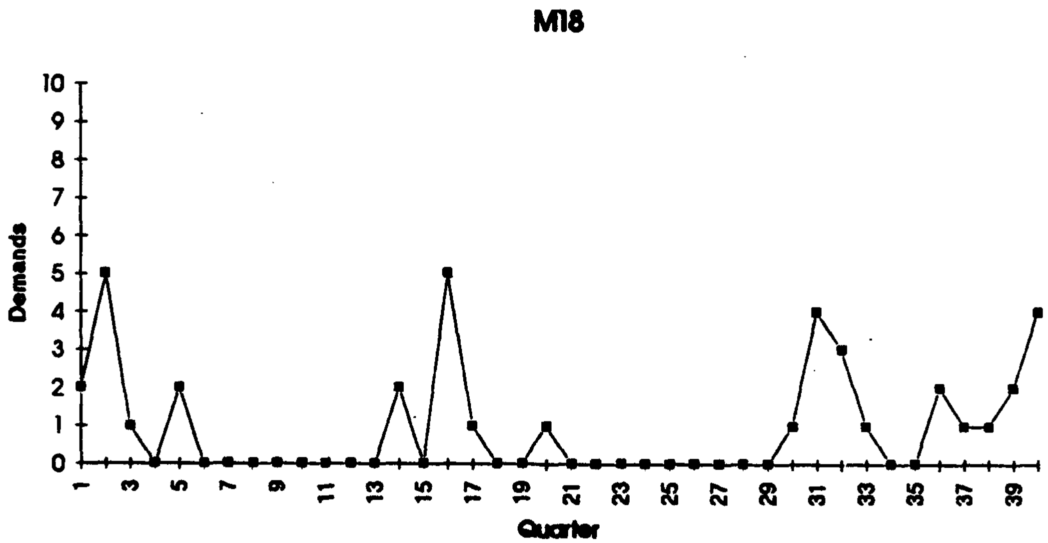

Figure 33. Demand Patterns for Item M18

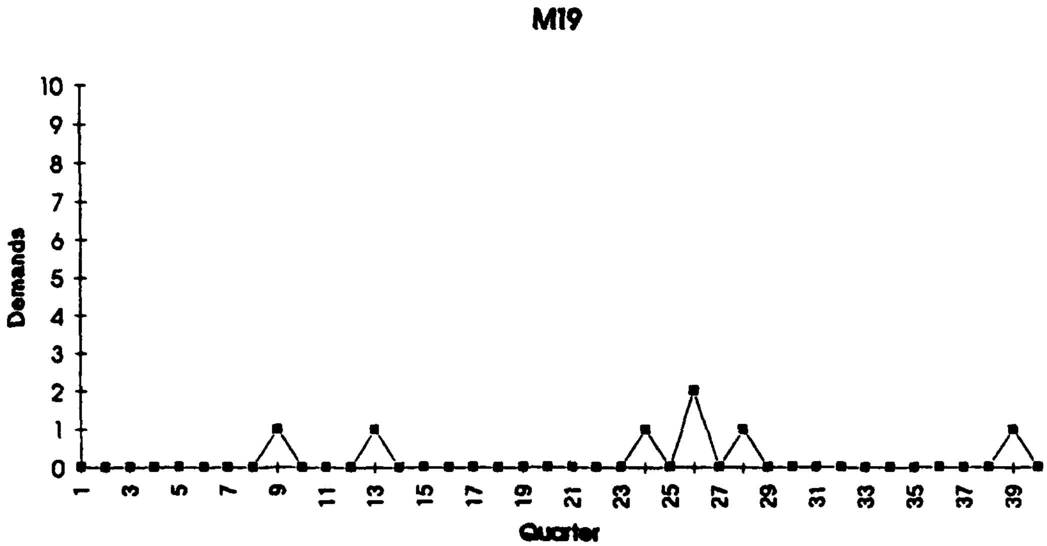

Figure 34. Demand Patterns for Item M19

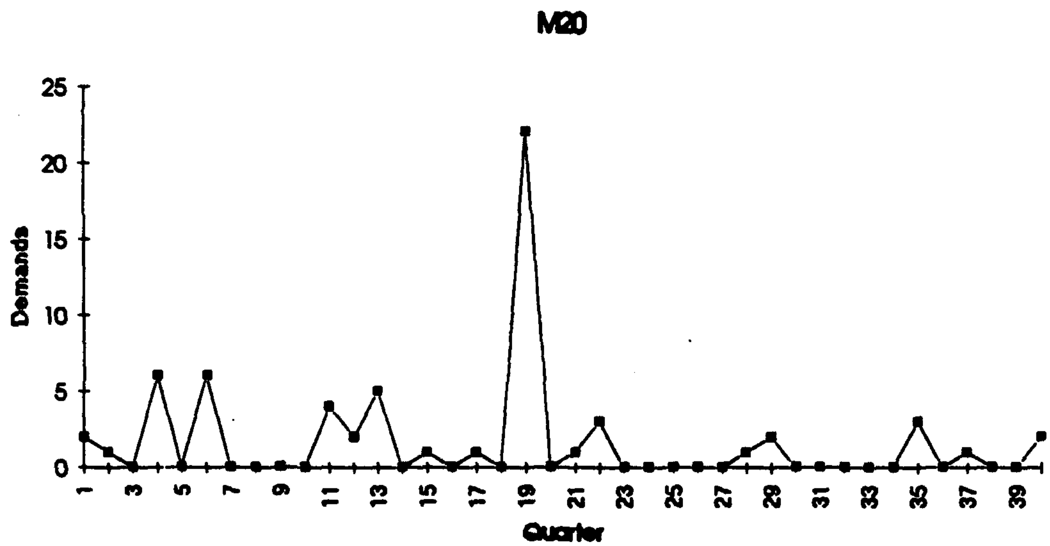

Figure 35. Demand Patterns for Item M20

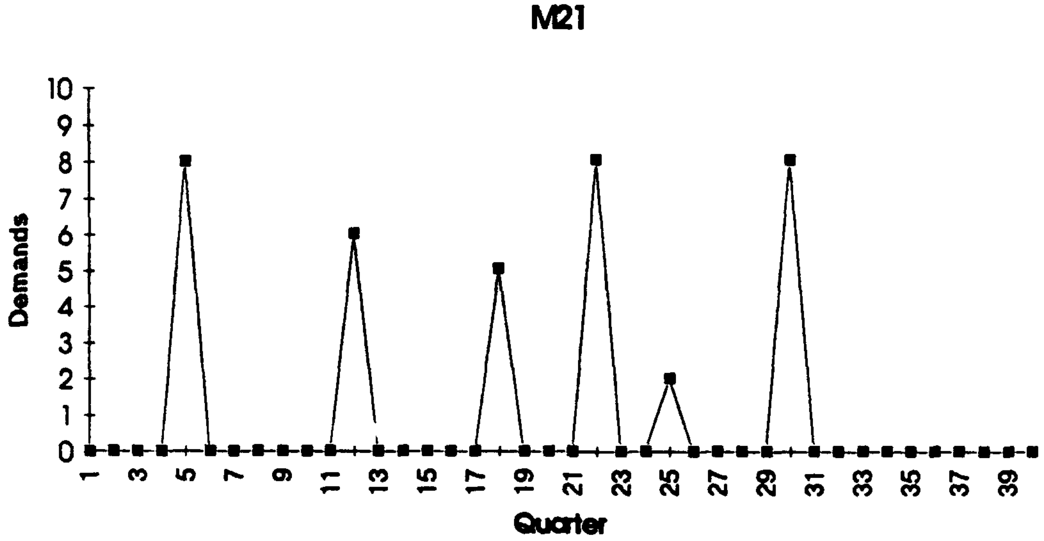

Figure 36. Demand Patterns for Item M21

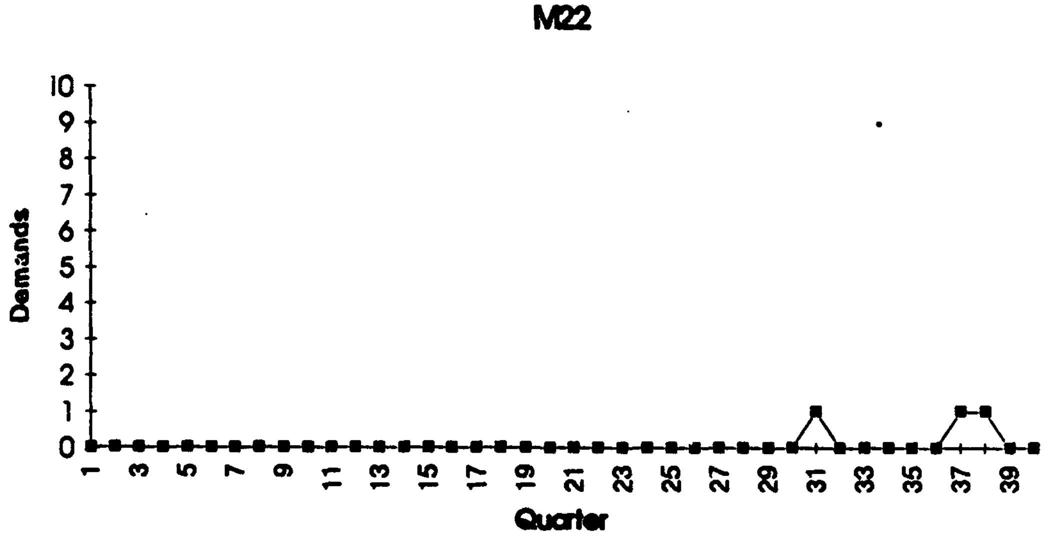

Figure 37. Demand Patterns for Item M22

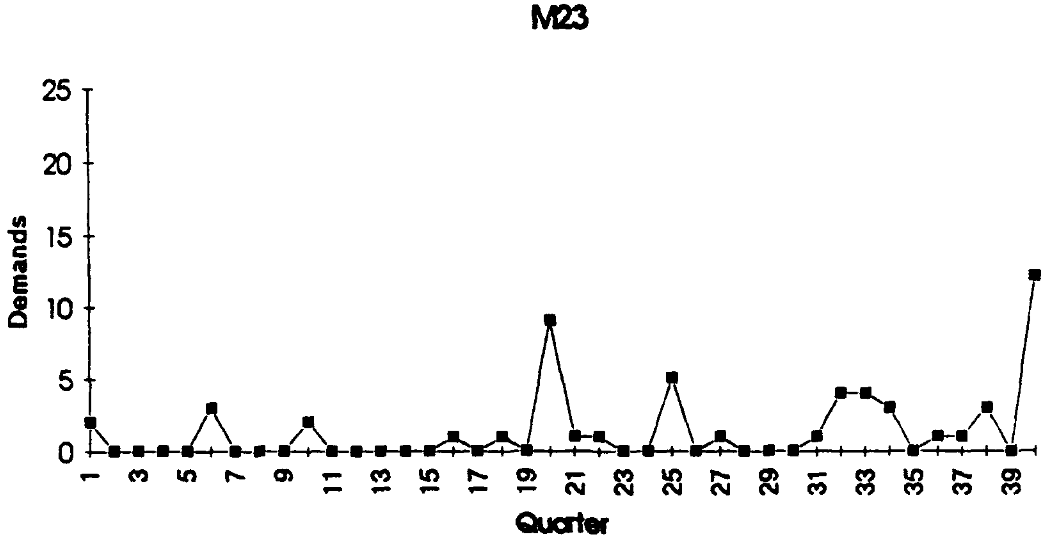

Figure 38. Demand Patterns for Item M23

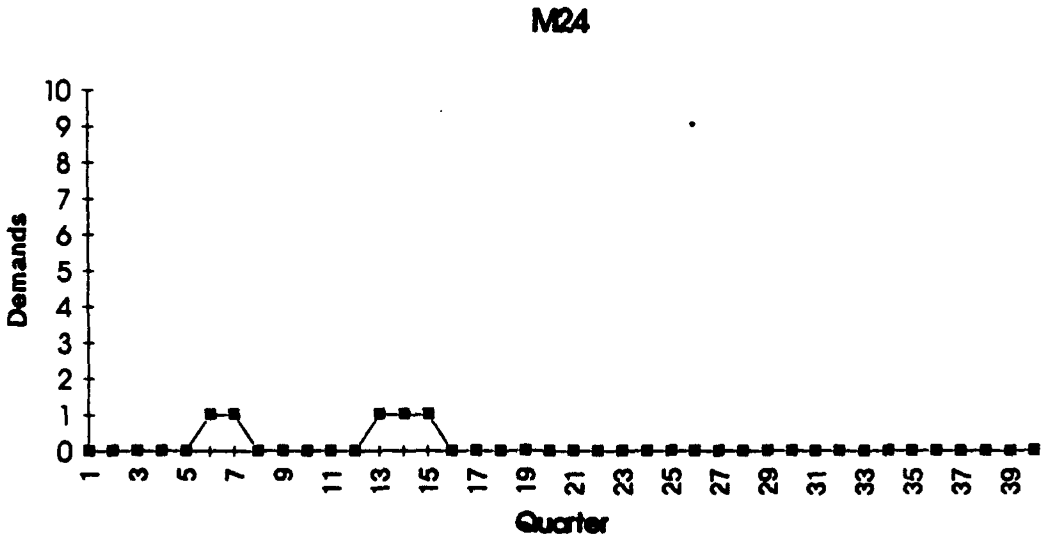

Figure 39. Demand Patterns for Item M24

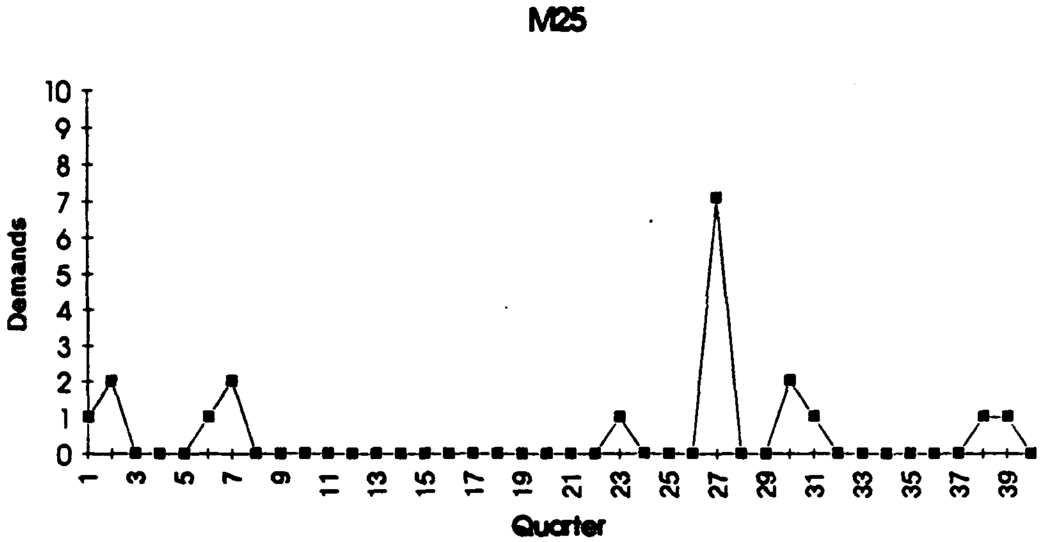

Figure 40. Demand Patterns for Item M25

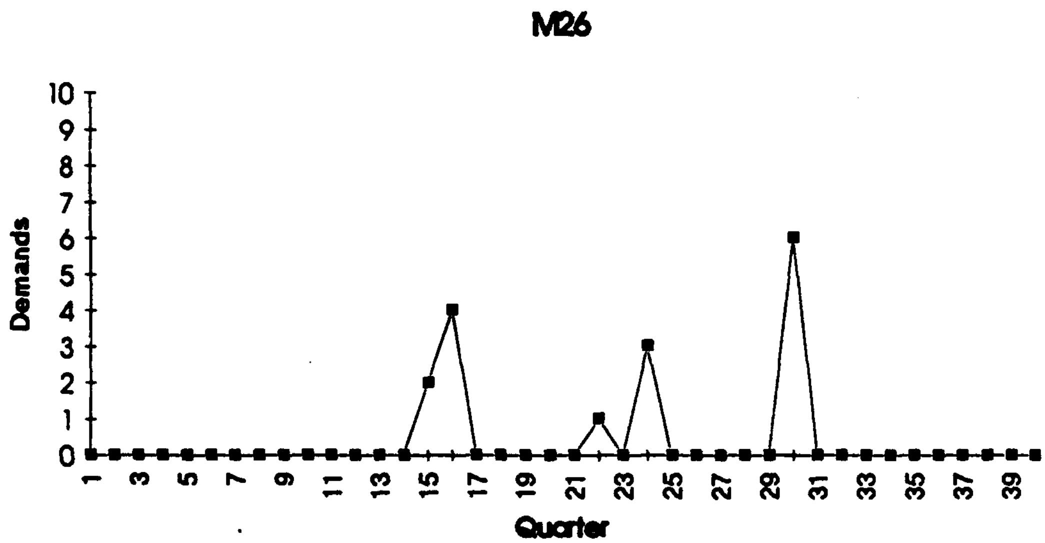

Figure 41. Demand Patterns for Item M26

Figure 42. Demand Patterns for Item M27

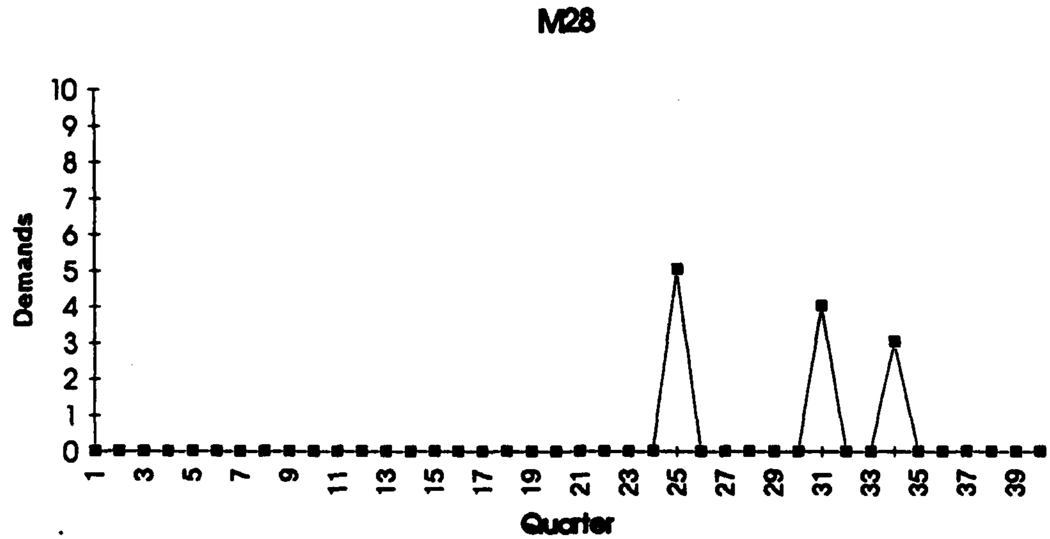

Figure 43. Demand Patterns for Item M28

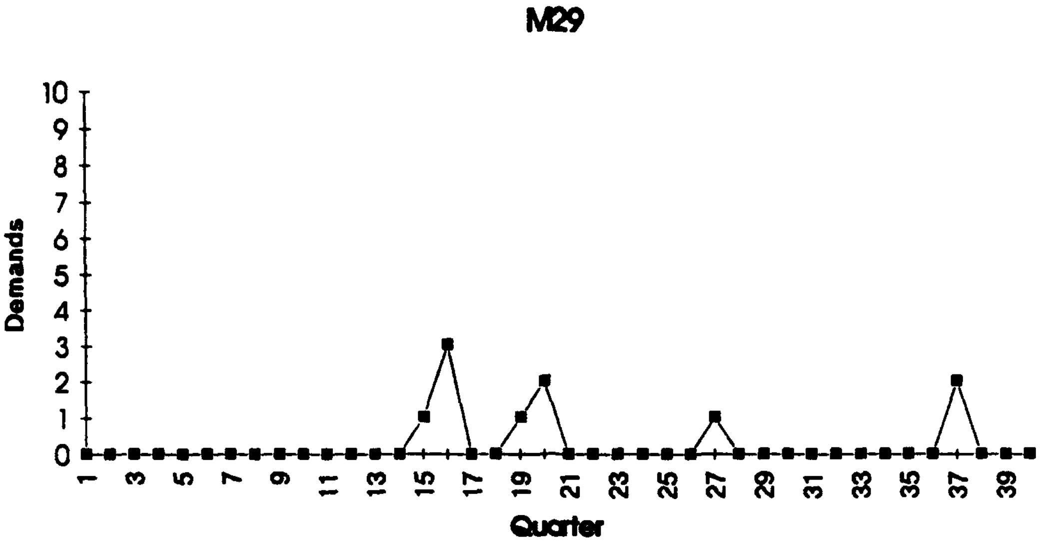

Figure 44. Demand Patterns for Item M29

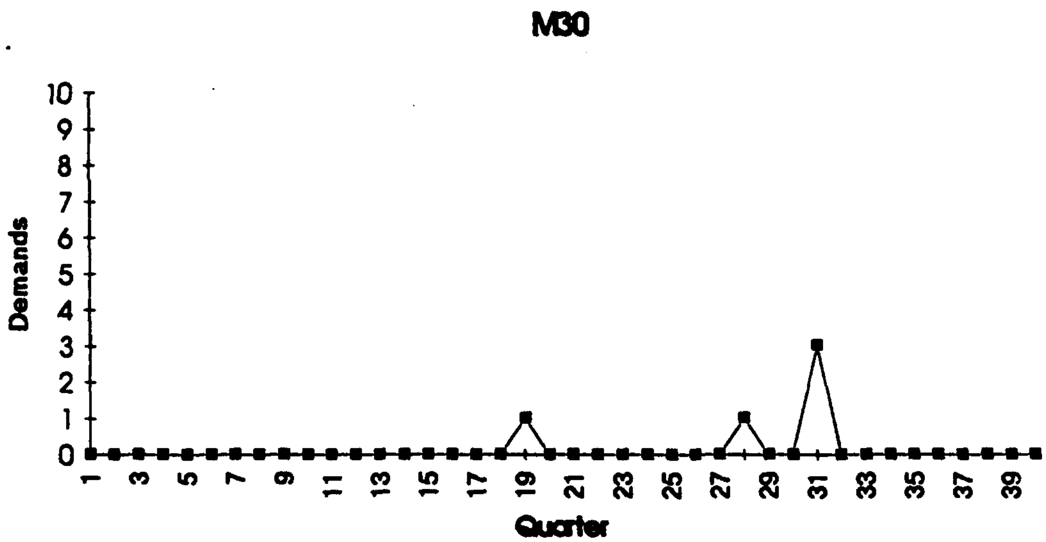

Figure 45. Demand Patterns for Item M30

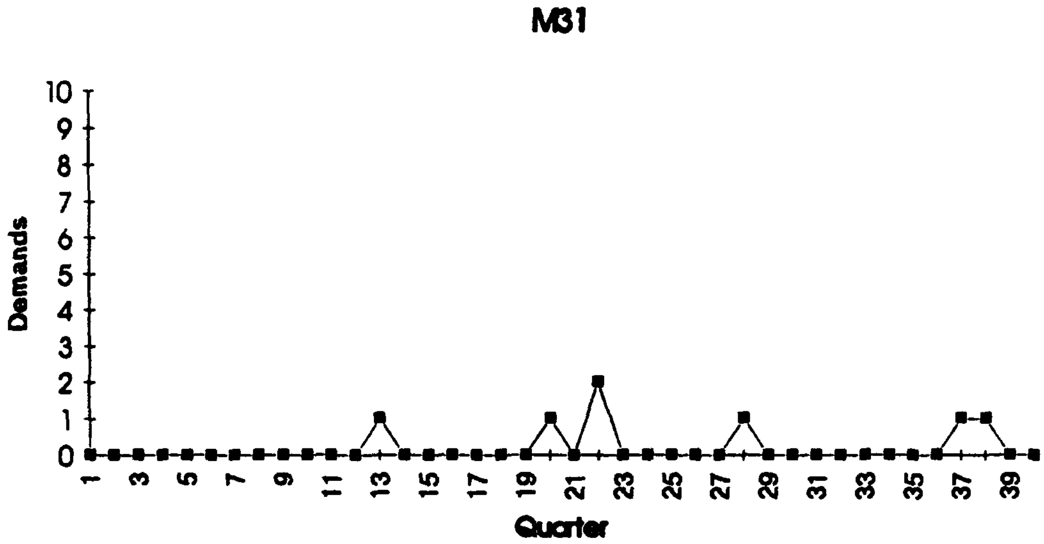

Figure 46. Demand Patterns for Item M31

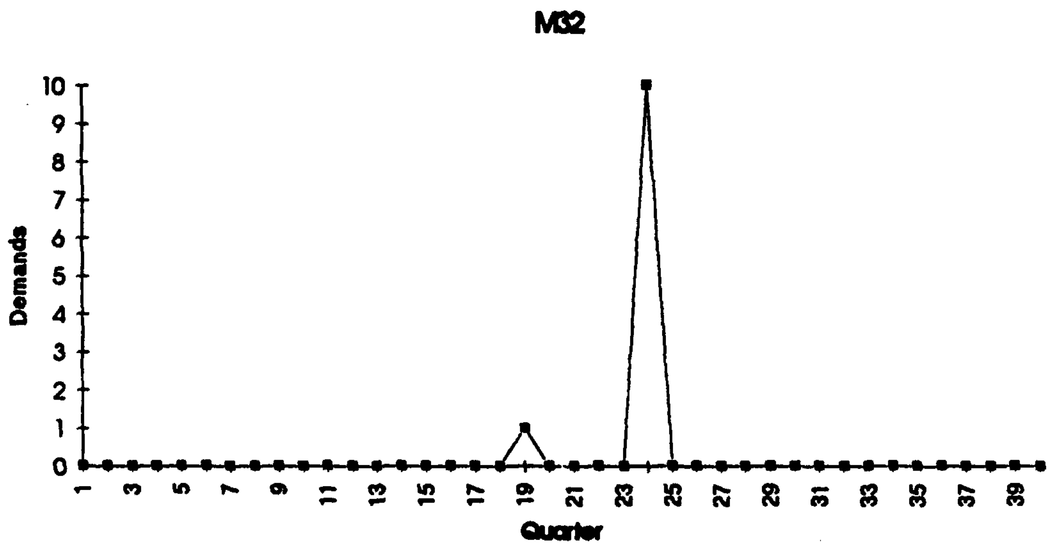

Figure 47. Demand Patterns for Item M32

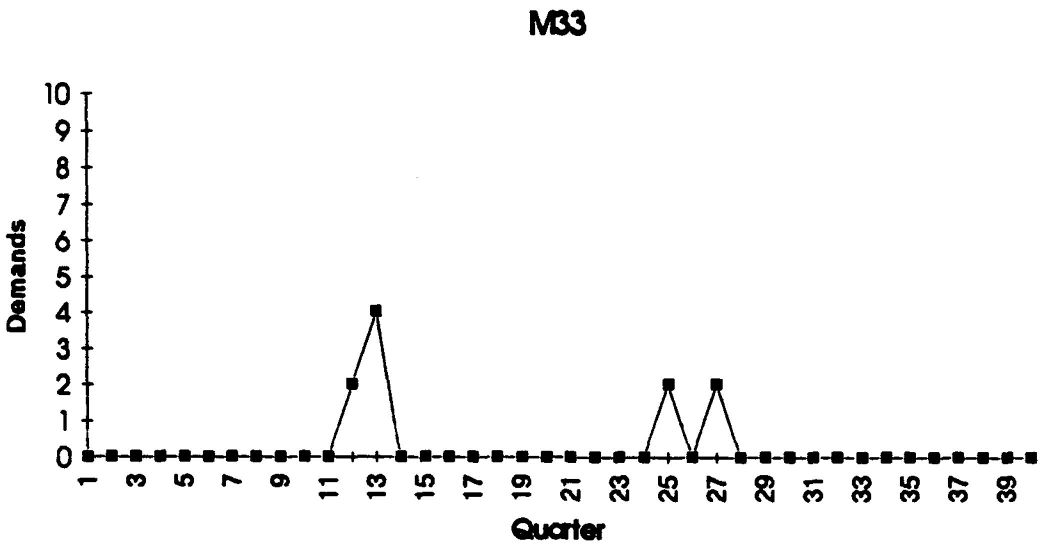

Figure 48. Demand Patterns for Item M33

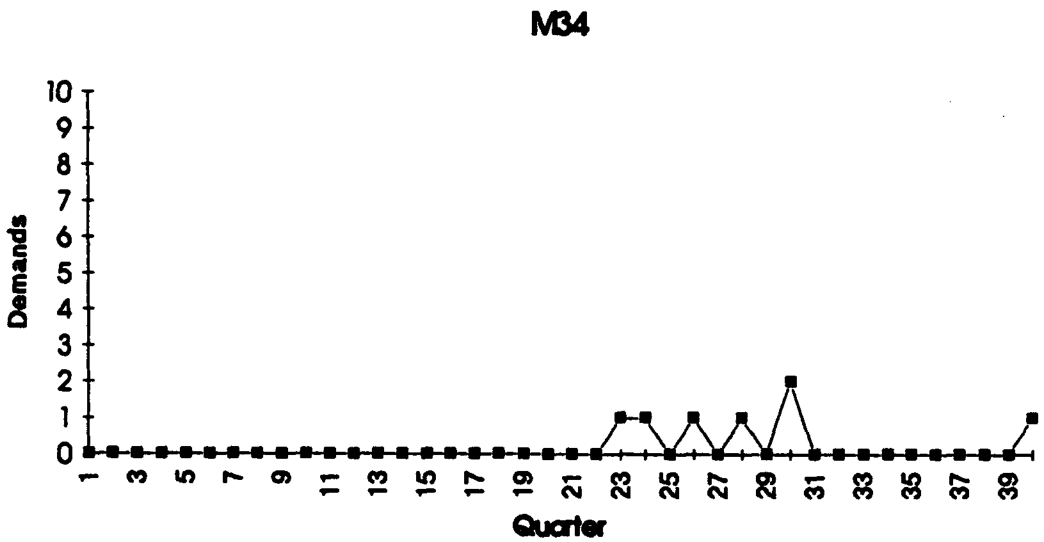

Figure 49. Demand Patterns for Item M34

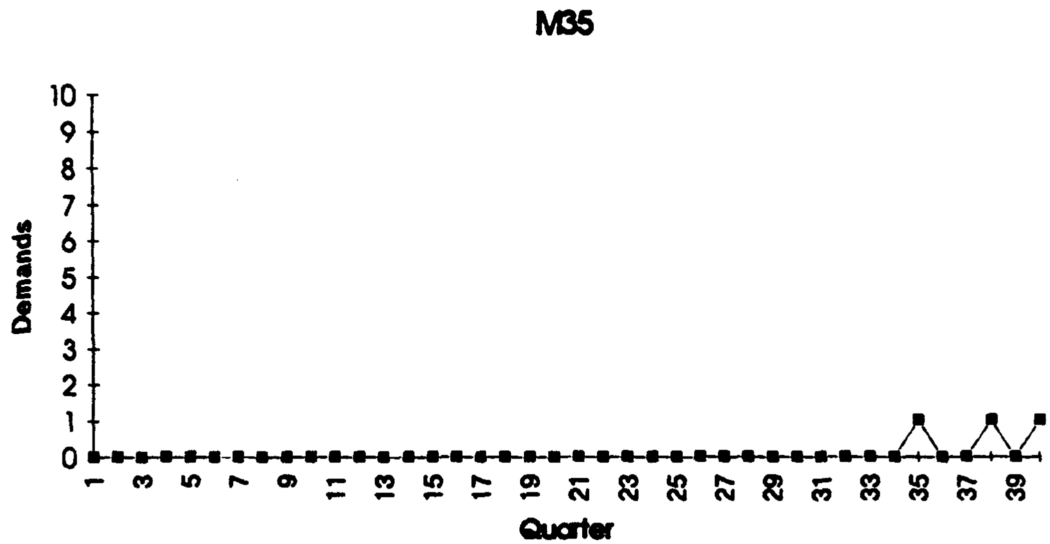

Figure 50. Demand Patterns for Item M35

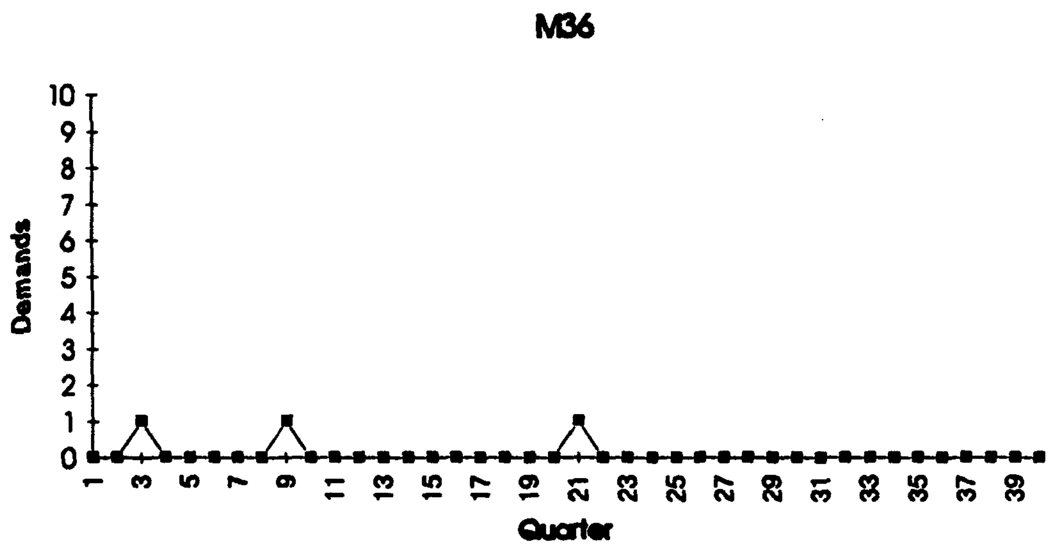

Figure 51. Demand Patterns for Item M36

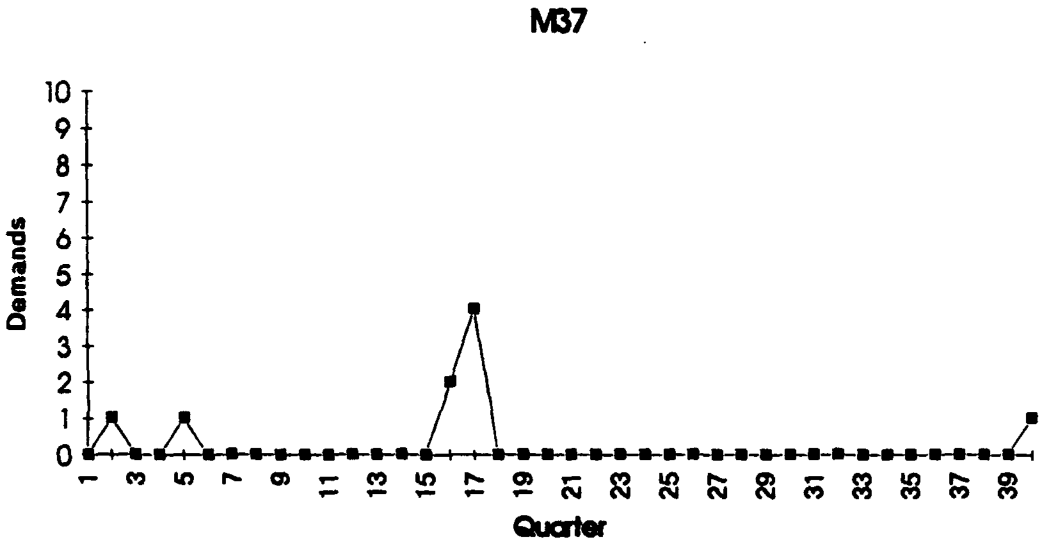

Figure 52. Demand Patterns for Item M37

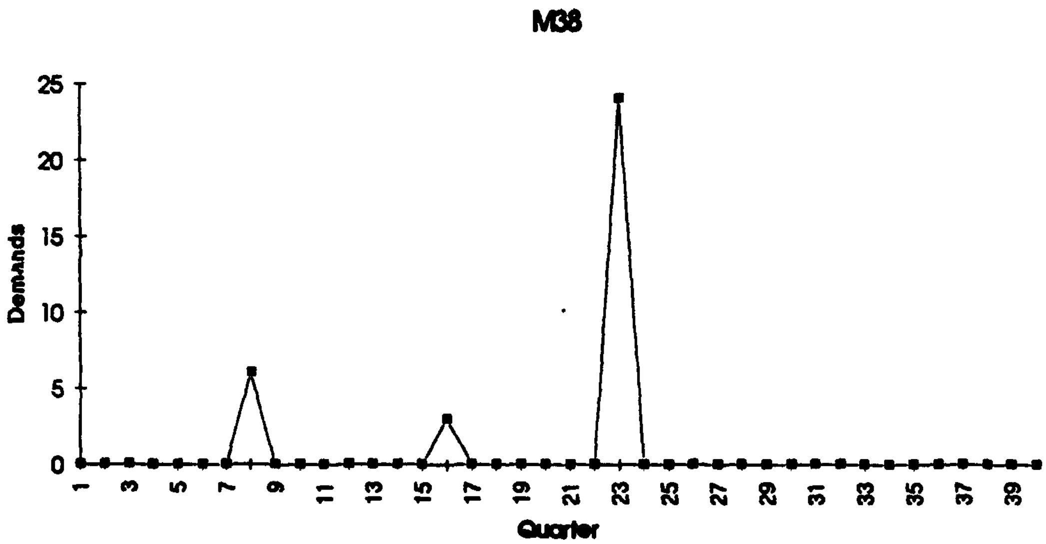

Figure 53. Demand Patterns for Item M38

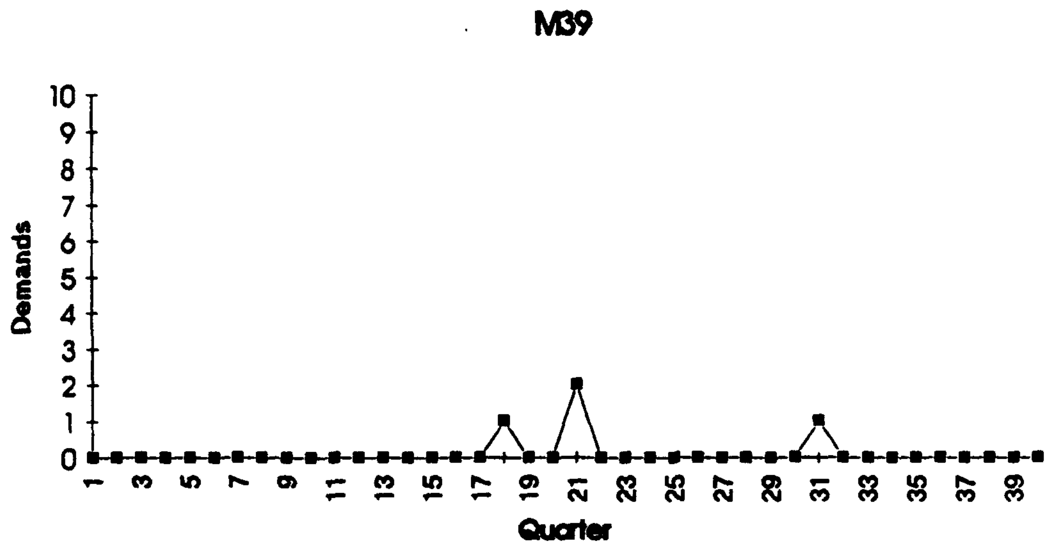

Figure 54. Demand Patterns for Item M39

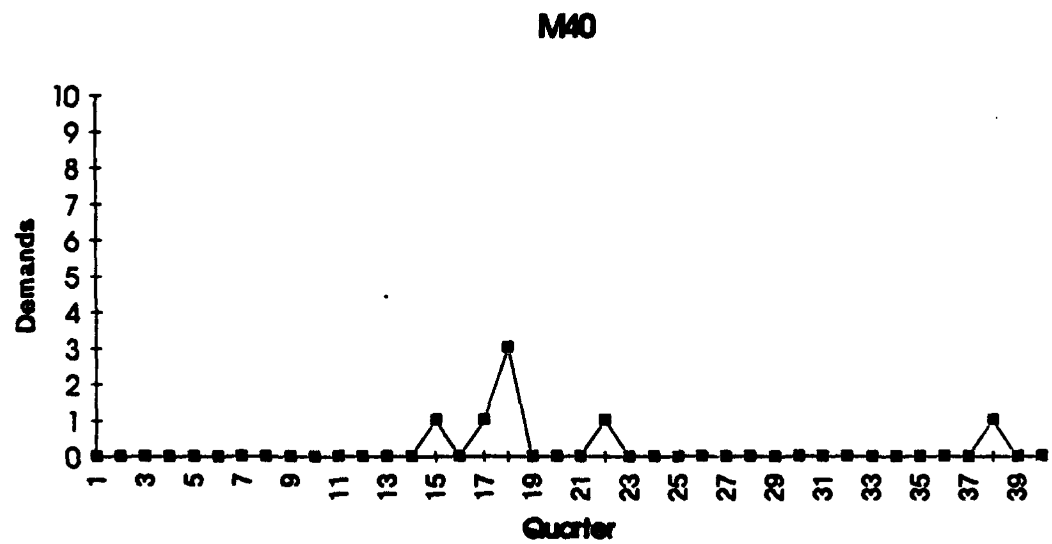

Figure 55. Demand Patterns for Item M40

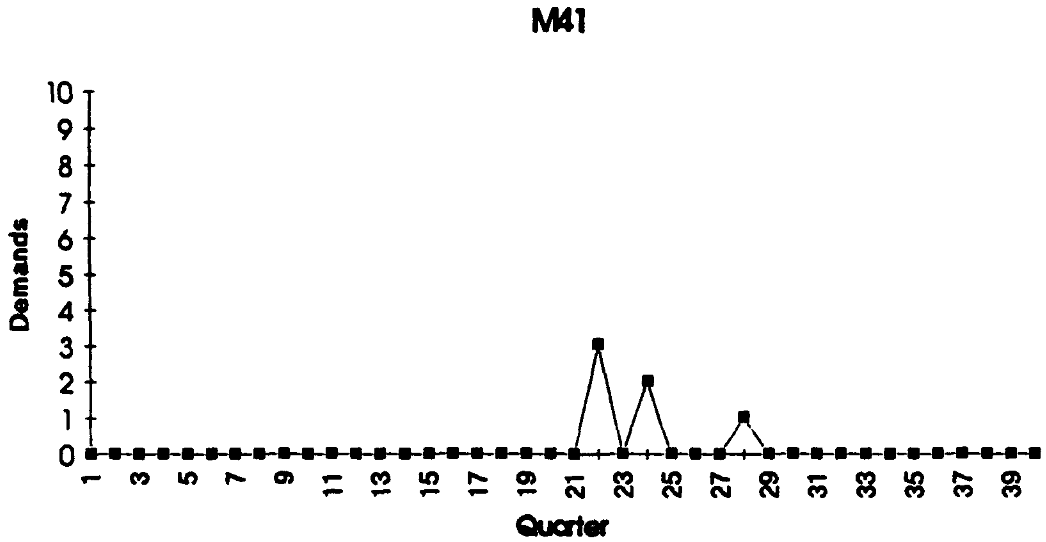

Figure 56. Demand Patterns for Item M41

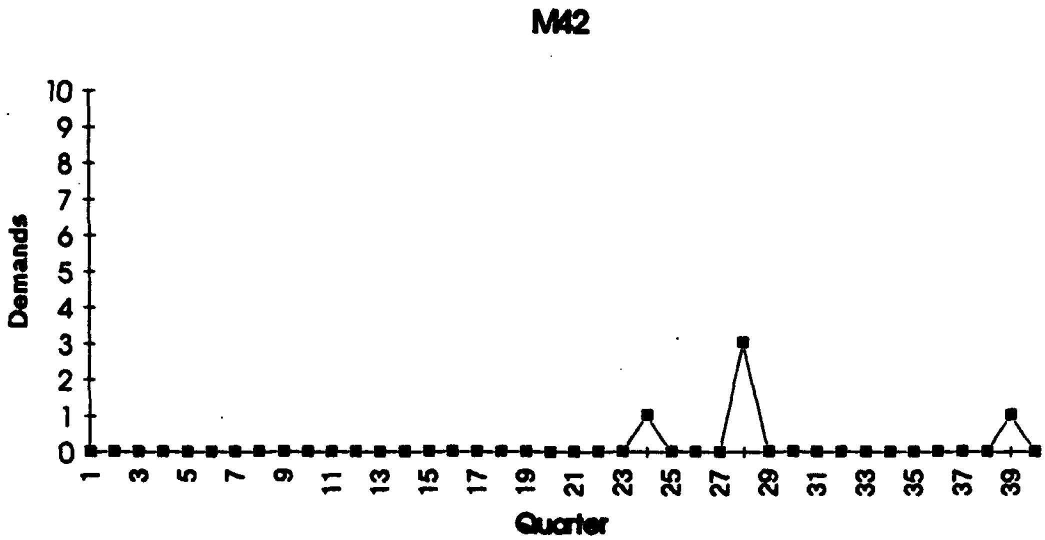

Figure 57. Demand Patterns for Item M42

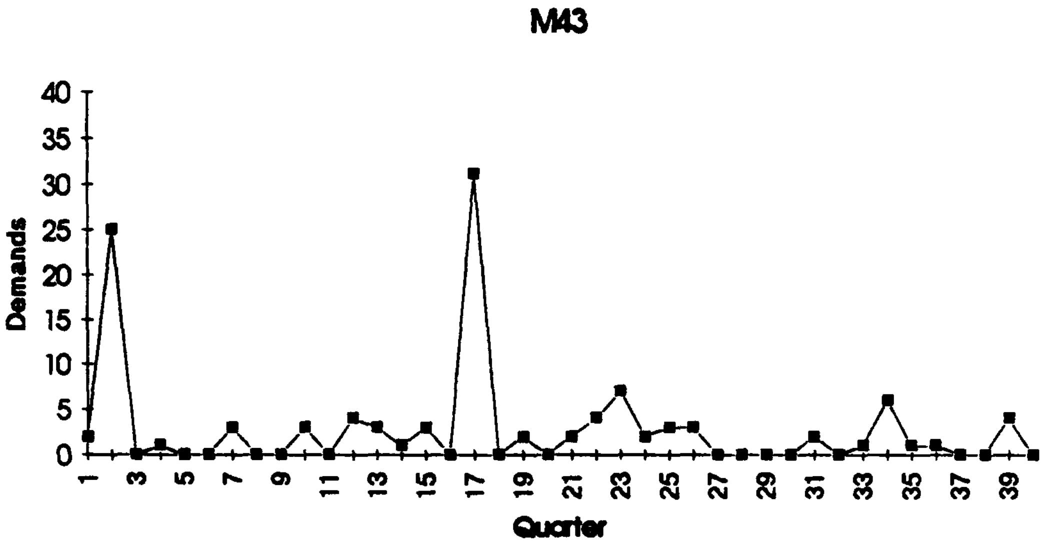

Figure 58. Demand Patterns for Item M43

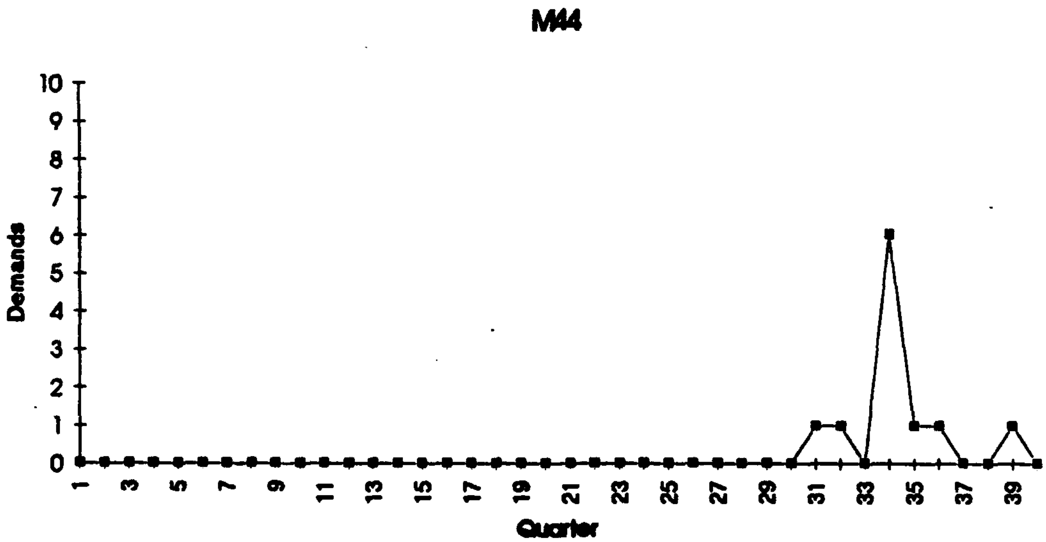

Figure 59. Demand Patterns for Item M44

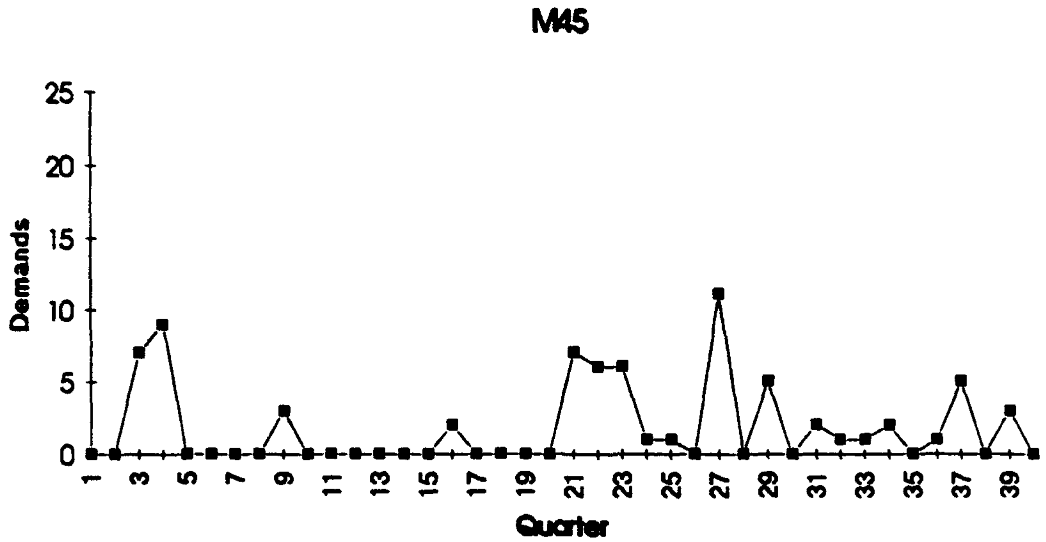

Figure 60. Demand Patterns for Item M45

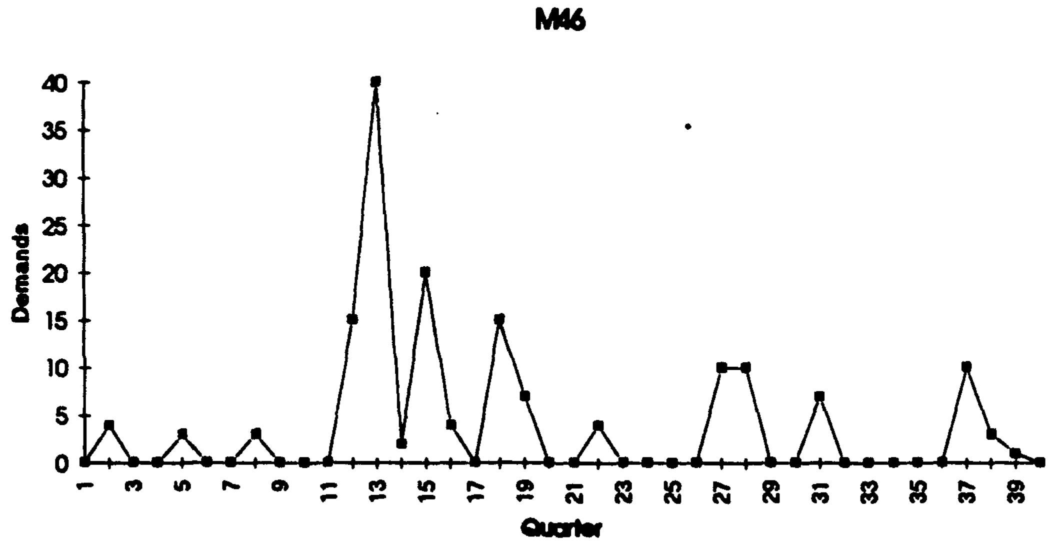

Figure 61. Demand Patterns for Item M46

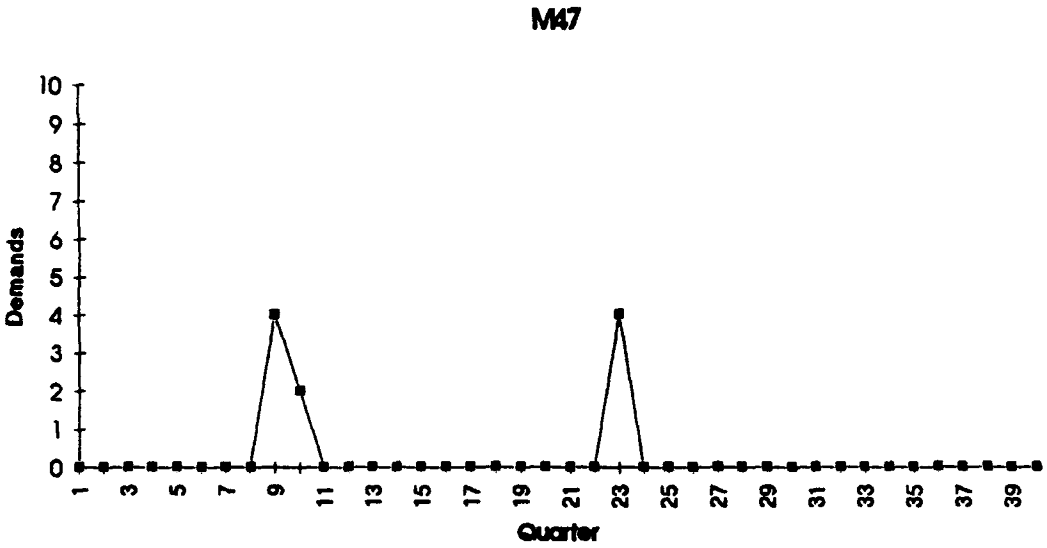

Figure 62. Demand Patterns for Item M47

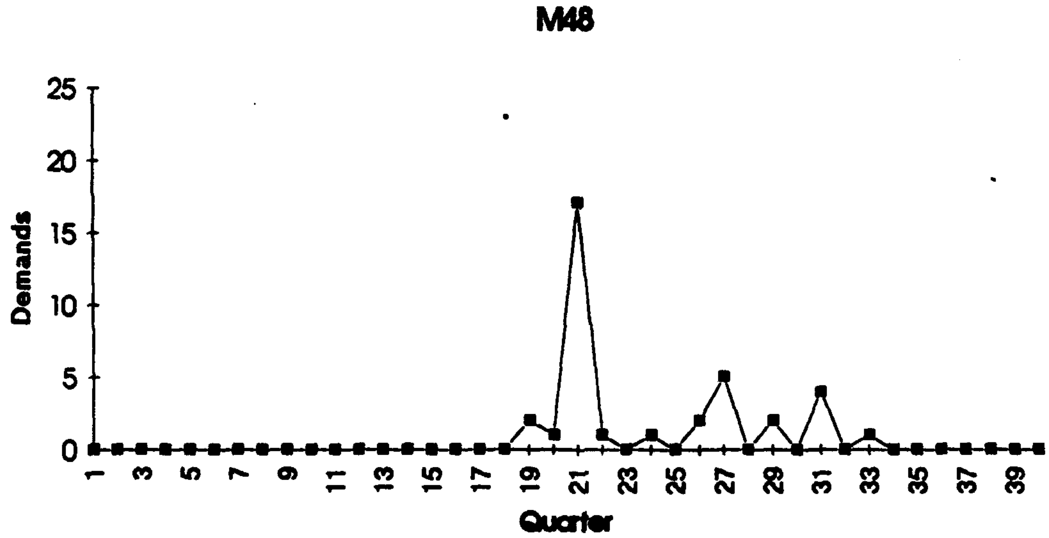

Figure 63. Demand Patterns for Item M48

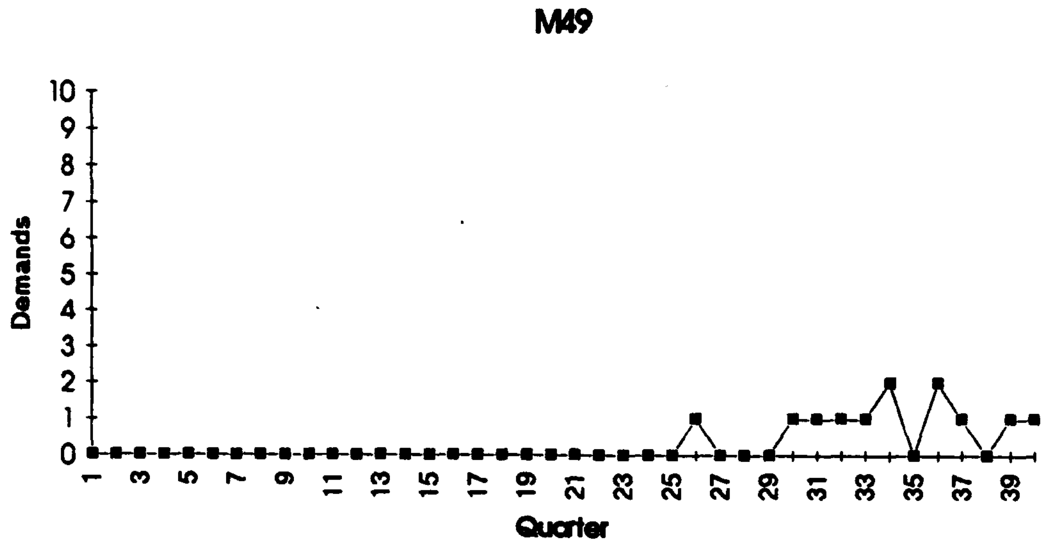

Figure 64. Demand Patterns for Item M49

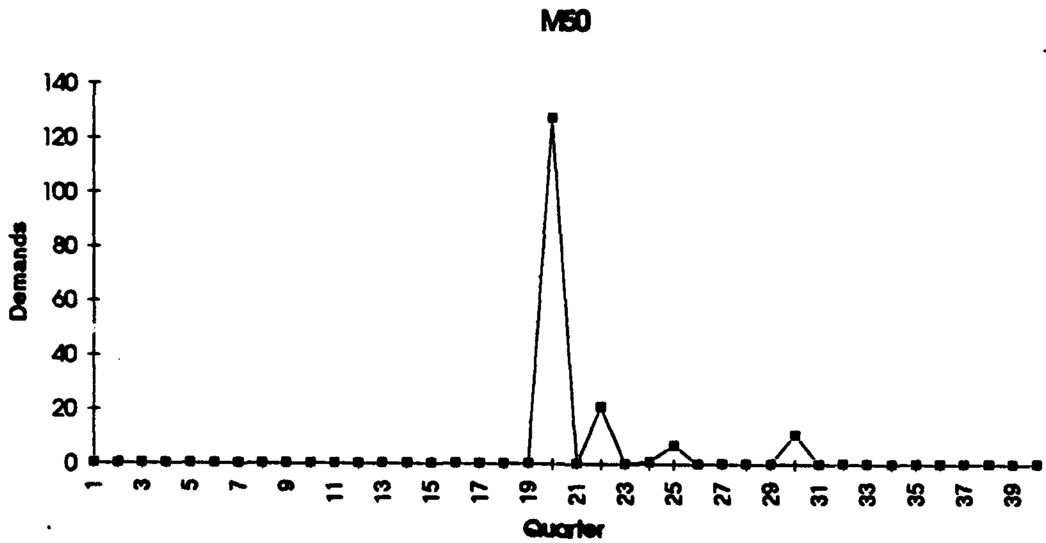

Figure 65. Demand Patterns for Item M50

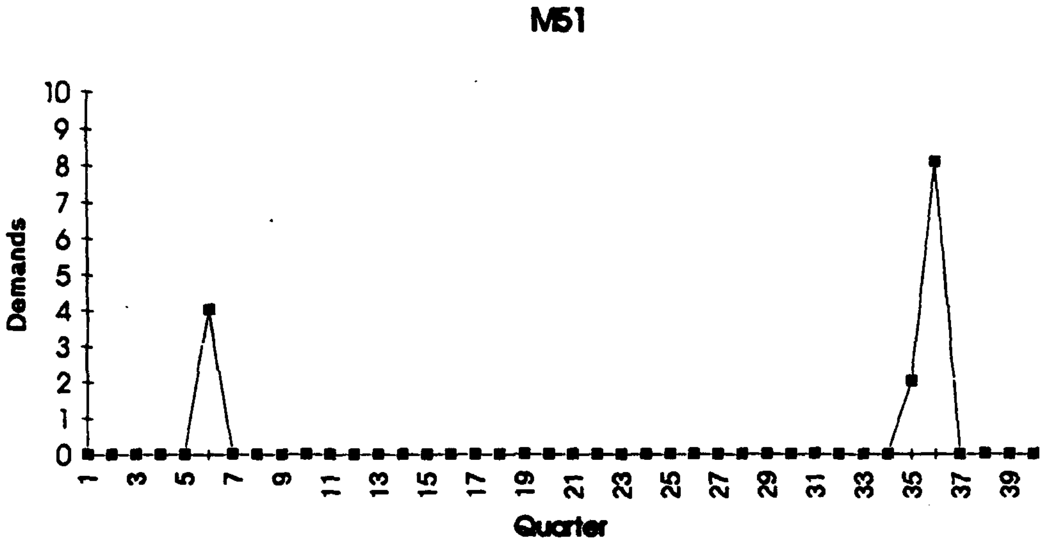

Figure 66. Demand Pattern for Item 51

Appendix C: Data Inputs

Sample of Data Input Format for
One Quarter Into the Future Forecasts

Quarter	Combined	H-coded	N-coded
1	8	7	1
2	9	0	9
3	5	4	1
4	6	2	4
5	5	5	0
6	7	5	2
7	4	4	0
8	3	1	2
9	2	1	1
10	5	5	0
11	8	2	6
12	0	0	0
13	2	0	2
14	3	3	0
15	0	0	0
16	7	5	2
17	1	1	0
18	1	1	0
19	2	2	0
20	2	2	0
21	1	0	1
22	4	2	2
23	2	2	0
24	2	2	0
25	3	0	3
26	2	1	1
27	2	2	0
28	1	1	0
29	5	4	1
30	2	2	0
31	4	4	0
32	5	0	5
33	1	1	0
34	0	0	0
35	3	2	1
36	0	0	0
37	8	7	1
38	5	4	1
39	7	7	0
40	11	2	9

Sample of Data Input Format for 24 Month Forecasts

Combination	H-coded	N-coded
47	28	19
41	22	19
37	27	10
40	25	15
34	23	11
31	18	13
27	16	11
23	12	11
27	16	11
26	16	10
22	12	10
16	12	4
18	14	4
17	14	3
18	13	5
20	15	5
15	12	3
17	11	6
18	11	7
18	11	7
17	10	7
21	14	7
19	14	5
21	16	5
24	14	10
22	15	7
20	14	6
21	14	7
20	13	7
23	16	7
26	18	8
29	21	8
35	23	12

Sample of Data Input Format for
36 Month Forecasts

Combined	H-coded	N-coded
62	36	26
56	29	27
50	32	18
45	28	17
46	31	15
42	27	15
36	23	13
34	21	13
33	22	11
32	21	11
31	18	13
25	18	7
27	20	7
28	20	8
27	18	9
29	20	9
23	16	7
27	19	8
28	20	8
30	22	8
33	20	13
33	21	12
29	19	10
30	19	11
28	17	11
33	24	9
36	27	9
41	32	9
51	33	18

Sample of Data Input Format for 9 Month H-coded Only Forecasts

H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
11	4	25	6	4	18	0	5	10	2
6	3	32	7	4	15	0	11	12	0
11	3	41	11	7	3	0	9	13	1
12	3	55	15	4	15	0	7	5	5
14	3	68	14	4	15	0	1	1	5
10	3	56	11	0	18	0	0	2	8
6	6	57	11	0	4	0	0	14	4
7	7	50	14	0	4	0	0	22	4
8	6	40	25	0	11	0	1	29	6
7	4	28	21	0	11	0	9	27	6
2	5	28	22	0	11	0	9	24	6
3	4	24	17	0	11	0	9	21	0
3	2	18	35	0	18	0	1	12	2
8	0	20	30	1	18	0	2	8	2
6	0	20	27	1	14	0	1	2	2
7	0	25	11	3	7	0	1	3	0
4	0	34	15	4	9	0	2	2	23
5	0	77	22	8	6	0	3	4	24
4	0	76	23	6	10	4	3	10	24
4	0	60	22	4	9	8	1	19	1
4	0	14	16	0	7	10	11	17	0
6	0	17	17	1	5	8	11	28	0
4	0	7	17	1	5	21	11	20	0
3	0	33	12	1	4	28	0	25	0
3	0	33	7	0	4	29	1	15	8
4	0	41	5	0	3	32	3	14	10
7	0	45	12	1	4	25	3	14	11
7	0	54	16	4	3	27	4	10	6
10	0	56	16	4	3	16	2	15	7
6	0	38	8	3	1	31	9	25	9
5	0	29	7	0	0	34	7	20	6
1	0	33	5	4	1	37	7	20	3
3	0	21	7	6	2	22	1	5	1
2	0	31	13	7	3	17	5	5	3
9	0	31	14	4	3	10	5	11	3
11	0	34	15	2	3	21	4	15	6
18	0	20	11	2	2	41	5	15	4
13	0	9	11	1	1	42	5	4	4

Appendix D: Data Outputs

One Quarter Into the Future Forecasts

NSN	Total H & N Coded Combined			H-Coded Only			N-Coded Only		
	Double Exp.	Adaptive Rate Exp. Smooth	Decomp.	Double Exp.	Adaptive Rate Exp. Smooth	Decomp.	Double Exp.	Adaptive Rate Exp. Smooth	Decomp.
H1	441.05	6.33	7.00	5.41	5.41	2.09	5.31	5.72	5.50
H2	4.73	4.44	2.48	0.61	0.61	0.18	2.24	N/A	0.98
H3	713.57	731.79	435.64	125.84	105.43	76.83	507.48	536.67	197.93
H4	19.76	17.89	10.99	15.76	N/A	10.13	0.61	N/A	0.38
H5	15.44	17.79	9.05	1.76	1.83	1.11	N/A	16.53	10.20
H6	285.20	293.39	146.02	14.26	14.31	12.70	280.59	N/A	133.24
H7	38.26	39.54	25.93	26.12	N/A	21.57	466.08	6.69	4.03
H8	9.60	10.22	5.71	7.37	7.87	4.19	0.45	N/A	0.27
H9	138.31	126.29	74.37	24.43	22.51	15.45	100.87	N/A	37.01
H10	311.64	325.54	222.34	15.51	18.29	5.76	306.21	319.50	219.70
H11	14.63	N/A	3.58	1.38	N/A	0.57	14.58	N/A	3.39
H12	57.23	55.57	42.87	N/A	31.08	22.17	26.46	27.96	14.72
H13	15.45	16.71	10.21	N/A	17.55	10.97	N/A	N/A	0.13
M1	0.11	N/A	0.07	0.11	N/A	0.07	N/A	N/A	0.00
M2	N/A	N/A	2.77	N/A	1.43	1.34	1.98	N/A	1.81
M3	555.18	0.65	0.39	0.27	560.49	0.18	0.34	0.39	0.16
M4	0.43	0.44	0.40	0.34	0.35	0.27	0.13	N\A	0.10
M5	N/A	N/A	0.96	0.10	N/A	0.08	0.95	N\A	0.80
M6	1.72	N/A	1.89	N/A	N/A	0.00	1.72	N\A	1.89
M7	0.23	N/A	0.18	0.23	N/A	0.18	N/A	N\A	0.00
M8	0.30	N/A	0.32	N/A	N/A	0.32	0.03	N\A	0.02
M9	0.53	N/A	0.47	0.10	N/A	0.09	563.85	N\A	0.38
M10	8.40	N/A	5.99	1.84	N/A	1.52	3.63	N\A	2.49
M11	0.14	0.14	0.07	0.08	N/A	0.07	0.03	N\A	0.00
M12	N/A	N/A	0.27	0.12	N/A	0.09	0.14	N\A	0.11
M13	0.15	0.16	0.14	0.15	0.16	0.14	N/A	N\A	0.00
M14	0.23	N/A	0.20	N/A	N/A	0.00	0.23	N\A	0.20
M15	0.44	N/A	0.39	N/A	N/A	0.00	0.44	N\A	0.39
M16	0.27	N/A	0.21	0.05	N/A	0.02	0.23	N\A	0.18
M17	N/A	2.21	1.95	1.10	1.08	0.81	1.39	1.44	1.13
M18	0.21	N/A	0.21	N/A	N/A	0.00	0.21	N/A	0.21
M19	13.99	15.94	13.08	2.52	2.65	2.32	10.66	N/A	9.33
M20	6.22	N/A	5.17	N/A	N/A	0.00	6.22	N/A	5.17

M21	0.07	N/A	0.06	0.07	N/A	0.06	N/A	N/A	0.00
M22	N/A	6.68	5.40	1.10	N/A	1.03	4.79	4.47	3.18
M23	0.12	N/A	0.09	0.07	N/A	0.07	0.05	N/A	0.04
M24	1.62	548.64	1.21	1.43	550.95	1.10	0.16	565.31	0.13
M25	1.62	N/A	1.43	N/A	N/A	0.00	1.62	N/A	1.43
M26	N/A	N/A	0.14	0.03	N/A	0.02	0.13	N/A	0.12
M27	N/A	N/A	1.09	N/A	N/A	0.00	N/A	N/A	1.09
M28	0.48	N/A	0.43	N/A	N/A	0.00	0.48	N/A	0.43
M29	0.28	N/A	0.23	0.25	N/A	0.20	0.03	N/A	0.02
M30	0.21	N/A	0.18	0.03	N/A	0.02	0.19	N/A	0.17
M31	2.59	N/A	2.44	N/A	N/A	0.00	2.59	N/A	2.44
M32	0.75	0.79	0.67	0.05	N/A	0.04	0.72	0.77	0.61
M33	0.70	N/A	0.59	0.10	N/A	0.09	0.61	N/A	0.49
M34	0.20	N/A	0.16	0.20	N/A	0.16	N/A	N/A	0.00
M35	N/A	N/A	0.06	N/A	N/A	0.06	N/A	N/A	0.00
M36	0.08	N/A	0.05	N/A	N/A	0.00	0.08	N/A	0.05
M37	N/A	0.60	0.48	N/A	N/A	0.00	N/A	0.60	0.48
M38	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M39	15.85	N/A	15.12	N/A	N/A	0.00	15.85	N/.A	15.12
M40	0.15	N/A	0.14	N/A	N/A	0.12	0.03	N/.A	0.02
M41	N/A	N/A	0.27	0.08	N/A	0.06	0.26	N/.A	0.23
M42	0.35	N/A	0.32	N/A	N/A	0.00	0.35	N/.A	0.32
M43	0.28	N/A	0.25	N/A	N/A	0.00	0.28	N/.A	0.25
M44	38.53	41.06	36.33	N/A	N/A	0.15	38.89	41.40	37.16
M45	0.97	N/A	0.77	0.43	N/A	0.33	N/A	N/A	0.14
M46	N/A	N/A	7.91	3.32	N/A	2.21	6.40	N/A	5.38
M47	65.39	62.91	57.05	N/A	N/A	7.61	60.09	56.89	56.09
M48	0.91	N/A	0.83	0.91	N/A	0.83	N/A	N/A	0.00
M49	8.47	N/A	7.48	N/A	N/A	1.10	4.09	N/A	3.75
M50	N/A	N/A	0.25	N/A	N/A	0.25	N/A	N/A	0.00
M51	N/A	N/A	406.07	N/A	N/A	12.56	413.60	N/A	371.97
M52	2.12	N/A	2.01	N/A	N/A	0.00	2.12	N/A	2.01
MSE Sum	2795.14	2325.70	1580.82	253.53	1341.99	219.30	2856.42	1584.33	1154.94
Observations	52.00	24.00	65.00	39.00	17.00	65.00	52.00	14.00	65.00
Average MSE	53.75	96.90	24.32	6.50	78.94	3.37	54.93	113.17	17.77
Percent Function	0.80	0.37	1.00	0.60	0.26	1.00	0.80	0.22	1.00

Comparison of Forecasts - Combined H & N Code 24-Month Mean Square Error

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
H1	31.29	37.06	36.29	41.06	44.41	65.12
H2	105.59	69.35	60.41	47.65	37.18	51.47
H3	6655.94	5246.59	5293.24	4981.24	4408.59	2545.65
H4	413.18	386.41	421.88	428.24	460.53	442.12
H5	406.24	381.41	360.59	361.69	355.88	398.24
H6	12161.24	10525.76	9960.82	9415.00	8794.41	6390.18
H7	2359.53	2507.94	2664.06	2867.88	3045.18	3638.35
H8	40.53	39.18	45.06	41.00	36.47	60.53
H9	6007.76	5586.71	5636.12	5630.59	5586.94	4561.41
H10	3171.06	2828.71	2405.53	2366.24	2366.00	2283.00
H11	787.47	699.24	686.41	645.94	596.24	382.47
H12	765.35	739.59	656.12	593.59	547.59	730.29
H13	343.94	295.71	295.00	298.35	297.41	352.35
M1	0.94	0.94	1.00	0.94	0.88	1.71
M2	37.82	31.65	31.12	27.29	26.47	7.88
M3	5.00	4.12	5.06	4.06	4.18	1.88
M4	10.59	10.00	12.41	11.59	12.24	5.76
M5	1.59	No Comp.	2.18	2.65	3.59	2.71
M6	120.88	112.24	117.24	116.24	115.59	135.82
M7	3.18	3.18	3.18	3.18	3.18	3.18
M8	8.59	8.53	8.53	8.76	8.82	8.65
M9	21.88	18.76	19.06	18.82	19.71	18.47
M10	120.59	121.18	126.65	133.94	137.24	133.18
M11	1.47	1.47	2.00	1.41	1.65	0.88
M12	10.18	10.18	10.18	10.18	10.18	10.18
M13	6.35	5.35	5.29	4.94	4.94	8.53
M14	3.76	3.88	3.47	3.35	3.35	3.41
M15	10.06	8.35	7.41	7.00	6.47	11.12
M16	8.76	8.76	8.76	8.76	8.76	8.76
M17	66.76	60.12	58.06	58.29	51.65	38.06
M18	10.06	8.41	8.18	7.88	7.24	6.00
M19	343.94	292.12	290.06	277.76	275.00	140.53
M20	33.82	31.65	32.53	31.94	31.82	29.82

M21	1.24	1.24	1.24	1.41	1.41	1.12
M22	96.00	79.18	76.12	74.59	66.24	78.12
M23	2.71	2.94	3.47	3.47	3.71	1.59
M24	58.59	52.12	50.00	49.00	47.71	40.94
M25	18.71	15.65	14.59	12.12	10.29	18.06
M26	3.59	3.41	3.41	3.12	3.35	3.94
M27	23.18	23.12	22.65	22.47	22.53	6.00
M28	0.00	0.00	0.00	0.00	0.00	10.06
M29	6.41	5.88	5.06	4.29	4.29	4.82
M30	3.59	3.59	3.18	3.29	3.29	1.82
M31	108.59	95.94	93.65	91.65	89.76	66.00
M32	6.35	5.59	6.29	6.24	6.35	6.29
M33	14.88	13.65	12.65	11.71	10.65	6.59
M34	13.12	11.53	11.94	12.00	11.76	9.12
M35	1.18	1.18	1.18	1.18	1.18	1.18
M36	0.71	0.71	0.71	0.65	0.65	0.71
M37	18.88	16.06	15.94	15.24	15.35	6.88
M38	N/A	N/A	N/A	N/A	N/A	N/A
M39	527.76	458.59	441.65	425.65	409.41	262.06
M40	4.06	3.41	3.24	3.00	3.29	4.00
M41	12.76	11.35	12.53	11.00	10.94	10.94
M42	16.35	19.24	20.00	19.59	20.12	24.71
M43	10.00	8.53	8.41	8.00	7.59	6.94
M44	529.59	455.76	455.65	447.65	452.71	210.35
M45	33.59	34.35	34.35	36.35	36.35	31.94
M46	293.88	276.12	283.53	291.76	296.41	236.59
M47	No Comp.	1630.59	1659.29	1644.82	1641.88	320.29
M48	14.59	12.71	11.59	10.53	9.24	6.76
M49	283.35	257.24	262.88	258.65	265.94	314.65
M50	16.59	17.53	17.53	20.12	20.12	14.82
M51	15798.94	13507.59	13209.47	12960.41	12734.00	17928.94
M52	29.65	29.65	29.65	29.65	29.71	29.76
MSE Sum	52024.18	47138.94	46045.71	44936.94	43546.00	42143.70
Observations	63.00	63.00	64.00	64.00	64.00	64.00
Average MSE	825.78	748.24	719.46	702.14	680.41	658.50

Comparison of Forecasts N-Coded Only 24-Month Mean Square Error						
	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
H1	12.88	10.12	11.00	10.88	12.00	13.94
H2	28.06	25.00	23.76	19.29	19.94	29.18
H3	4657.29	4042.71	4144.59	4128.24	3932.65	3650.00
H4	7.29	6.24	6.82	6.06	6.29	1.82
H5	329.88	330.35	316.71	320.76	320.71	340.00
H6	12965.82	11359.88	10909.00	10425.06	9895.88	11427.71
H7	196.24	179.88	173.18	170.88	168.35	195.06
H8	10.65	9.35	9.18	8.88	9.35	6.53
H9	4058.76	3957.12	4101.06	4218.06	4309.41	3196.06
H10	3490.12	3277.06	2446.71	2318.41	2263.24	1981.88
H11	866.41	766.53	745.12	694.35	633.29	438.12
H12	612.06	476.65	476.71	461.06	450.76	135.35
H13	No Comp.	4.06	3.76	3.53	3.53	2.65
M1	No Data	No Data	No Data	No Data	No Data	No Data
M2	58.82	54.47	57.82	59.00	61.88	22.88
M3	1.18	1.18	1.00	0.94	0.94	1.88
M4	0.82	0.82	0.88	0.88	0.94	0.82
M5	0.18	0.47	0.76	1.24	2.18	1.76
M6	120.88	112.24	117.24	116.24	115.59	135.82
M7	No Data	No Data	No Data	No Data	No Data	No Data
M8	No Comp.	0.24	0.24	0.24	0.24	0.24
M9	No Comp.	11.24	11.06	10.59	10.41	15.18
M10	36.71	35.47	35.82	35.76	35.35	55.94
M11	No Data	No Data	No Data	No Data	No Data	No Data
M12	3.18	3.18	3.18	3.18	3.18	3.18
M13	No Data	No Data	No Data	No Data	No Data	No Data
M14	3.82	3.88	3.47	3.35	3.35	3.41
M15	10.06	8.35	7.41	7.00	6.47	11.12
M16	3.71	3.71	3.71	3.71	3.71	3.71
M17	29.65	25.24	25.76	24.65	24.00	15.00
M18	10.06	8.41	8.18	7.88	7.24	6.00
M19	271.71	224.47	208.71	195.88	186.35	117.12
M20	33.82	31.65	32.53	31.94	31.82	29.82

M21	No Data	No Data	No Data	No Data	No Data	No Data
M22	81.65	76.41	73.41	70.06	61.71	62.41
M23	0.00	0.00	0.00	0.00	0.06	0.06
M24	0.18	0.18	0.18	0.18	0.24	0.18
M25	18.71	15.65	14.59	12.12	10.29	18.06
M26	3.24	2.94	2.71	2.47	2.47	4.41
M27	23.18	23.12	22.65	22.47	22.53	24.35
M28	0.53	0.53	0.00	0.00	0.00	10.06
M29	8.24	0.76	0.76	0.71	0.71	1.47
M30	3.41	3.47	3.12	3.35	3.59	1.65
M31	108.59	95.94	93.65	91.65	89.76	66.00
M32	5.35	5.24	5.00	5.06	5.65	6.35
M33	8.41	8.00	7.88	7.59	8.00	3.53
M34	No Data	No Data	No Data	No Data	No Data	No Data
M35	No Data	No Data	No Data	No Data	No Data	No Data
M36	0.71	0.71	0.71	0.65	0.65	0.71
M37	18.88	16.06	15.94	15.24	15.35	6.88
M38	N/A	N/A	N/A	N/A	N/A	N/A
M39	527.76	458.59	441.65	425.65	409.41	No Comp.
M40	0.59	0.59	0.59	0.53	0.53	0.94
M41	8.35	6.76	7.00	6.35	6.59	7.18
M42	20.53	19.24	20.00	19.59	20.12	No Comp.
M43	10.00	8.53	8.41	8.00	7.59	No Comp.
M44	499.00	430.35	428.18	421.88	429.94	185.88
M45	7.82	8.00	8.00	8.82	8.82	7.35
M46	296.41	276.12	283.53	291.76	296.41	246.88
M47	No Comp.	2048.53	2197.18	2287.24	2385.47	625.76
M48	No Data	No Data	No Data	No Data	No Data	No Data
M49	123.12	112.00	109.88	108.82	108.24	158.29
M50	No Data	No Data	No Data	No Data	No Data	No Data
M51	13417.76	11385.18	10918.29	10545.18	10203.00	18256.53
M52	29.65	29.65	29.65	29.65	29.71	No Comp.
MSE Sum	43042.12	40002.47	38578.29	37672.94	36645.88	41537.12
Observations	51.00	55.00	55.00	55.00	55.00	51.00
Average MSE	843.96	727.32	701.42	684.96	666.29	814.45

Comparison of Forecasts - Combined H & N Code 36-Month Mean Square Error						
	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
H1	No Comp.	146.08	143.46	154.23	170.08	166.08
H2	40.69	28.62	29.92	27.46	27.85	73.92
H3	4416.00	4174.31	4198.77	4215.00	4155.31	4637.77
H4	1499.31	1388.08	1451.92	1452.92	1461.15	1164.77
H5	442.77	420.15	403.08	408.85	399.00	521.62
H6	10680.69	9353.62	8514.62	7714.62	6808.85	8912.92
H7	9097.38	9716.23	10145.85	10628.62	11048.69	10790.00
H8	96.15	74.54	72.62	70.08	68.54	120.77
H9	7403.85	7046.08	6996.00	6914.31	6832.46	7469.92
H10	No Comp.	3531.92	3401.23	3345.00	3204.23	3603.77
H11	443.62	407.77	414.77	403.23	388.54	383.38
H12	1112.77	1103.46	1099.31	1088.62	1100.00	1203.77
H13	578.23	574.77	607.62	648.15	670.46	863.77
M1	0.69	0.69	0.69	0.62	0.62	2.77
M2	63.08	57.69	59.15	57.15	59.15	21.08
M3	8.03	8.31	9.54	9.23	10.15	3.23
M4	25.08	24.00	27.15	26.46	28.31	12.92
M5	14.23	13.92	15.08	15.38	17.38	5.92
M6	189.08	177.46	177.69	171.00	164.54	342.15
M7	4.15	4.15	4.15	4.15	4.15	4.15
M8	23.92	21.08	21.08	21.54	21.92	20.31
M9	No Comp.	39.00	38.38	36.92	36.85	56.08
M10	325.69	324.00	332.15	351.31	362.31	203.00
M11	4.54	4.54	5.15	4.77	5.38	2.92
M12	13.31	13.31	13.31	13.31	13.31	13.31
M13	7.62	7.62	7.54	7.54	7.54	9.46
M14	3.62	3.69	3.92	4.15	4.15	9.62
M15	8.00	12.46	7.85	8.15	8.15	11.62
M16	11.46	11.46	11.46	11.46	11.46	11.46
M17	51.77	41.62	32.92	28.85	25.92	52.46
M18	5.08	5.08	4.23	4.23	3.85	6.69
M19	314.15	565.92	547.62	521.54	493.15	302.31

M20	51.69	45.77	44.54	43.00	41.08	49.69
M21	2.85	2.85	2.85	2.85	2.85	2.85
M22	64.38	No Comp.	63.85	70.00	72.85	113.15
M23	8.38	9.62	11.54	11.54	11.69	4.54
M24	75.85	73.77	70.31	68.38	66.00	72.46
M25	13.69	10.46	9.69	9.08	10.15	35.77
M26	4.23	4.23	4.15	3.85	3.85	9.92
M27	58.23	58.92	59.85	61.46	62.69	6.69
M28	22.46	18.85	19.00	17.54	18.23	30.62
M29	7.23	7.23	7.23	8.00	8.00	5.77
M30	6.46	5.38	5.23	4.85	4.69	3.85
M31	120.54	105.62	99.08	94.62	89.38	113.62
M32	15.62	15.62	14.69	15.85	14.00	17.54
M33	4.92	4.92	4.54	4.31	5.15	5.31
M34	18.15	18.23	18.23	19.31	19.69	20.77
M35	1.54	1.54	1.54	1.54	1.54	1.54
M36	0.62	0.62	0.62	0.62	0.69	0.85
M37	35.23	31.23	31.15	29.08	28.23	17.62
M38	N/A	N/A	N/A	N/A	N/A	N/A
M39	335.77	495.69	458.00	417.77	372.92	400.92
M40	5.69	4.38	4.31	4.31	4.31	8.62
M41	24.00	21.92	22.08	20.69	20.23	30.92
M42	26.46	24.31	23.85	22.77	22.38	54.92
M43	12.15	11.77	11.77	11.92	11.92	12.08
M44	1313.08	606.54	1099.92	1048.85	961.85	478.69
M45	53.54	53.54	53.54	53.54	53.54	53.54
M46	550.00	493.15	488.54	477.31	456.08	512.54
M47	3616.62	3215.23	3271.15	3248.08	3239.08	865.85
M48	7.62	10.46	8.69	7.62	7.38	16.23
M49	490.62	453.31	449.92	441.92	440.08	773.08
M50	44.62	44.62	44.62	45.92	45.92	37.23
M51	22664.08	19548.54	18753.62	17968.23	17098.15	44133.77
M52	41.23	41.23	41.54	42.00	42.31	39.08
MSE Sum	66582.54	64741.15	63997.85	62645.62	60850.38	88933.92
Observations	61.00	63.00	64.00	64.00	64.00	64.00

Comparison of Forecasts N-Coded Only 36-Month Mean Square Error

	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
H1	22.08	24.92	24.23	27.00	30.77	31.15
H2	37.85	36.15	39.54	42.38	43.62	49.85
H3	2588.54	2637.54	2835.00	3098.31	3249.85	3795.08
H4	19.85	17.00	17.92	17.77	17.92	3.69
H5	449.23	413.92	394.85	390.31	370.62	453.77
H6	13743.15	12350.62	11608.38	10891.85	10131.85	22392.92
H7	387.08	426.92	429.77	453.85	462.00	538.85
H8	14.62	12.54	11.77	11.15	10.62	13.46
H9	6587.15	5585.62	6099.00	6056.00	5934.46	5062.54
H10	3869.62	3396.31	3315.15	3248.77	3057.77	3675.92
H11	401.15	372.92	382.23	374.15	366.15	510.08
H12	1272.92	1077.85	1071.69	989.38	934.31	310.00
H13	4.15	3.62	3.38	3.92	3.92	4.54
M1	No Data	No Data	No Data	No Data	No Data	No Data
M2	148.23	141.23	146.31	147.54	154.15	64.62
M3	0.92	0.92	0.92	0.85	0.77	2.08
M4	1.38	1.38	1.46	1.46	1.54	1.08
M5	13.62	13.92	15.08	15.38	17.38	4.62
M6	189.08	177.46	177.69	171.00	164.54	342.15
M7	No Data	No Data	No Data	No Data	No Data	No Data
M8	No Comp.	0.31	0.31	0.31	0.31	0.31
M9	25.77	22.38	21.85	20.77	20.23	44.85
M10	82.54	80.69	84.54	92.92	97.46	61.23
M11	No Data	No Data	No Data	No Data	No Data	No Data
M12	4.15	4.15	4.15	4.15	4.15	4.15
M13	No Data	No Data	No Data	No Data	No Data	No Data
M14	3.62	3.69	3.92	4.15	4.15	9.62
M15	8.00	12.46	7.85	8.15	8.15	11.62
M16	4.85	4.85	4.85	4.85	4.85	4.85
M17	55.69	52.69	53.31	51.62	50.46	44.23
M18	5.08	5.08	4.23	4.23	3.85	6.69
M19	370.08	307.77	288.62	269.69	253.00	224.92
M20	51.69	45.77	44.54	43.00	41.08	49.69

M21	No Data	No Data	No Data	No Data	No Data	No Data
M22	32.23	32.08	27.54	28.31	28.77	60.69
M23	0.62	0.69	1.00	1.00	1.08	0.15
M24	No Comp.	0.46	0.54	0.54	0.85	0.31
M25	13.69	10.46	9.69	9.08	10.15	35.77
M26	3.38	2.62	2.38	2.15	2.15	10.23
M27	58.23	58.92	59.85	61.46	62.69	71.08
M28	22.46	18.85	19.00	17.54	18.23	30.62
M29	1.00	1.00	1.00	0.92	0.92	1.62
M30	7.54	5.92	5.77	5.23	5.23	3.77
M31	120.54	105.62	99.08	94.62	89.38	113.62
M32	13.69	13.08	12.85	13.54	12.38	17.46
M33	11.38	11.38	12.15	13.08	15.23	8.62
M34	No Data	No Data	No Data	No Data	No Data	No Data
M35	No Data	No Data	No Data	No Data	No Data	No Data
M36	0.62	0.62	0.62	0.62	0.69	0.85
M37	35.23	31.23	31.15	29.08	28.23	17.62
M38	N/A	N/A	N/A	N/A	N/A	N/A
M39	335.77	495.69	458.00	417.77	372.92	No Comp.
M40	0.77	0.77	0.77	0.77	0.77	0.77
M41	15.15	13.08	13.08	12.15	12.15	19.85
M42	26.46	24.31	23.85	22.77	22.38	No Comp.
M43	12.15	11.77	11.77	11.92	11.92	No Comp.
M44	1275.31	1120.77	1078.46	1018.85	930.00	436.62
M45	14.46	14.46	14.46	14.46	14.46	14.46
M46	492.54	493.15	508.15	521.38	528.69	536.46
M47	5917.69	5587.15	5802.54	5907.08	5992.62	1954.69
M48	No Data	No Data	No Data	No Data	No Data	No Data
M49	186.92	167.38	158.15	149.69	143.62	414.62
M50	No Data	No Data	No Data	No Data	No Data	No Data
M51	18823.15	16129.00	15203.38	14339.08	13495.00	47023.38
M52	41.23	41.23	41.54	42.00	42.31	No Comp.
MSE Sum	57824.31	51622.38	50689.31	49180.00	47282.77	88491.76
Observations	53.00	55.00	55.00	55.00	55.00	51.00
Average MSE	1091.02	938.59	921.62	894.18	859.69	1735.13

Comparison of Forecasts H-Coded Only 3-Quarter Mean Square Error						
	Double Exp.	Single Exp.	Moving Average 2	Moving Average 3	Moving Average 4	AFSAC Method
H1	29.59	27.59	26.82	27.73	23.95	33.27
H2	No Comp.	8.36	20.68	16.95	13.82	8.59
H3	1326.41	992.64	956.59	899.23	804.36	425.00
H4	53.73	60.41	62.05	45.14	38.95	55.18
H5	18.14	14.91	13.41	12.73	11.55	9.86
H6	8.36	10.91	13.09	12.82	12.05	14.45
H7	258.18	215.73	193.41	177.55	157.86	2880.77
H8	10.95	10.95	24.36	22.86	22.27	14.77
H9	62.23	113.14	109.55	110.73	107.45	66.23
H10	74.18	76.45	150.82	141.18	123.23	80.23
H11	4.05	7.64	7.27	6.50	6.68	5.50
H12	162.86	151.59	141.77	144.36	152.36	185.14
H13	105.23	86.09	93.09	100.86	104.91	85.14
M1	0.45	0.45	0.50	0.41	0.45	0.50
M2	10.77	11.82	10.50	9.36	8.73	7.59
M3	0.82	0.82	1.00	0.77	1.05	0.50
M4	0.68	0.68	0.95	0.86	1.14	0.64
M5	No Comp.	1.09	0.95	0.82	0.82	0.68
M6	No Data	No Data	No Data	No Data	No Data	No Data
M7	No Comp.	2.45	2.23	1.86	1.64	1.77
M8	No Comp.	3.23	3.14	2.95	2.32	3.09
M9	1.55	1.09	1.00	0.91	1.09	0.77
M10	No Comp.	9.59	9.55	7.18	7.45	8.86
M11	0.18	0.23	0.23	0.18	0.23	0.09
M12	0.82	0.86	0.82	0.77	0.77	0.77
M13	No Comp.	1.36	1.50	1.36	1.41	1.32
M14	No Data	No Data	No Data	No Data	No Data	No Data
M15	No Data	No Data	No Data	No Data	No Data	No Data
M16	No Comp.	No Comp.	0.23	0.18	0.18	0.23
M17	15.14	11.86	11.32	11.36	9.82	8.36
M18	No Data	No Data	No Data	No Data	No Data	No Data
M19	2.55	2.68	3.36	3.59	4.00	1.68
M20	No Data	No Data	No Data	No Data	No Data	No Data

M21	0.59	0.68	0.64	0.64	0.50	0.64
M22	6.50	6.73	6.09	5.73	4.64	5.41
M23	0.05	0.23	0.64	0.41	0.59	0.36
M24	10.55	9.00	8.59	8.18	8.77	6.09
M25	No Data	No Data	No Data	No Data	No Data	No Data
M26	0.27	0.27	0.32	0.27	0.32	0.32
M27	No Data	No Data	No Data	No Data	No Data	No Data
M28	No Data	No Data	No Data	No Data	No Data	No Data
M29	1.64	2.73	2.73	2.36	2.36	1.82
M30	0.14	0.14	0.14	0.14	0.14	0.14
M31	No Data	No Data	No Data	No Data	No Data	No Data
M32	0.14	0.27	0.32	0.27	0.32	0.32
M33	1.55	1.09	1.00	0.91	1.09	0.77
M34	1.50	1.64	1.45	1.41	1.59	1.27
M35	0.18	0.18	0.18	0.23	0.23	0.18
M36	No Data	No Data	No Data	No Data	No Data	No Data
M37	No Data	No Data	No Data	No Data	No Data	No Data
M38	N/A	N/A	N/A	N/A	N/A	N/A
M39	No Data	No Data	No Data	No Data	No Data	No Data
M40	0.77	0.77	0.82	0.86	1.05	0.59
M41	0.45	0.50	0.50	0.41	0.45	0.45
M42	No Data	No Data	No Data	No Data	No Data	No Data
M43	No Data	No Data	No Data	No Data	No Data	No Data
M44	1.32	1.68	1.77	1.45	1.50	1.18
M45	3.41	5.73	5.73	5.27	4.64	5.05
M46	0.00	0.00	0.00	0.00	0.00	0.09
M47	56.32	97.55	92.14	89.64	83.64	56.59
M48	5.68	4.36	4.00	3.82	3.45	2.55
M49	15.14	12.64	12.82	11.36	11.45	10.59
M50	1.45	1.32	1.27	1.27	1.55	1.45
M51	139.41	121.73	115.95	110.64	105.55	43.23
M52	No Data	No Data	No Data	No Data	No Data	No Data
MSE Sum	2393.91	2093.86	2117.27	2006.50	1854.36	4040.09
Observations	42.00	48.00	49.00	49.00	49.00	49.00
Average MSE	57.00	43.62	43.21	40.95	37.84	82.45

Appendix E: Financial Comparison

High Demands

Item	NSN Value	Double Forecast	Actual Demand	AFSAC Forecast	Current Qty	Double $	AFSAC $	Actual $	Current Value
H1	13230.38	18	35	20	24	238146.84	264607.60	463063.30	317529.12
H2	4857.80	22	14	16	28	106871.60	77724.80	68009.20	136018.40
H3	2917.11	208	185	206	193	606758.88	600924.66	539665.35	563002.23
H4	2311.98	42	30	37	25	97103.16	85543.26	69359.40	57799.50
H5	2141.11	10	14	18	1	21411.10	38539.98	29975.54	2141.11
H6	398.55	166	7	59	8	66159.30	23514.45	2789.85	3188.40
H7	4744.91	69	94	69	39	327398.79	327398.79	446021.54	185051.49
H8	16153.67	17	10	13	10	274612.39	209997.71	161536.70	161536.70
H9	1055.46	189	62	107	33	199481.94	112934.22	65438.52	34830.18
H10	138.32	167	18	136	156	23099.44	18811.52	2489.76	21577.92
H11	1275.45	16	35	28	10	20407.20	35712.60	44640.75	12754.50
H12	4534.96	85	63	87	39	385471.60	394541.52	285702.48	176863.44
H13	1009.13	43	38	43	9	43392.59	43392.59	38346.94	9082.17
Total		1052	605	839	575	2410314.83	2233643.70	2217039.33	1681375.16

Medium Demands

Item	NSN Value	Double Forecast	Actual	AFSAC Forecast	Round Down	Round Up	Double $	AFSAC Dn $	AFSAC Up $	Actual $	Current Qty	Current Value
M1	674.53	1	1	0.2	0	1	674.53	0.00	674.53	674.53	2	1349.06
M2	3844.86	7	2	4	4	4	26914.02	15379.44	15379.44	7689.72	2	7689.72
M3	1904.50	3	2	1	1	1	5713.50	1904.50	1904.50	3809.00	1	1904.50
M4	2627.40	0	3	1	1	1	0.00	2627.40	2627.40	7882.20	3	7882.20
M5	6817.04	0	2	0.03	0	1	0.00	0.00	6817.04	13634.08	2	13634.08
M6	539.93	11	1	5	5	5	5939.23	2699.65	2699.65	539.93	6	3239.58
M7	382.04	0	3	0	0	0	0.00	0.00	0.00	1146.12	1	382.04
M8	3520.73	2	8	2	2	2	7041.46	7041.46	7041.46	28165.84	1	3520.73
M9	2625.87	0	0	0.43	0	1	0.00	0.00	2625.87	0.00	2	5251.74
M10	696.20	7	20	9	9	9	4873.40	6265.80	6265.80	13924.00	9	6265.80
M11	3723.67	0	0	0.09	0	1	0.00	0.00	3723.67	0.00	3	11171.01
M12	1371.65	0	7	0	0	0	0.00	0.00	0.00	9601.55	5	6858.25
M13	849.39	0	0	2	2	2	0.00	1698.78	1698.78	0.00	8	6795.12
M14	1254.99	1	0	1	1	1	1254.99	1254.99	1254.99	0.00	2	2509.98
M15	328.63	4	4	1	1	1	1314.52	328.63	328.63	1314.52	5	1643.15
M16	5131.48	0	5	0	0	0	0.00	0.00	0.00	25657.40	6	30788.88
M17	1283.49	1	11	4	4	4	1283.49	5133.96	5133.96	14118.39	2	2566.98
M18	1023.08	4	1	2	2	2	4092.32	2046.16	2046.16	1023.08	3	3069.24
M19	857.82	6	6	7	7	7	5146.92	6004.74	6004.74	5146.92	10	8578.20
M20	555.71	12	0	7	7	7	6668.52	3889.97	3889.97	0.00	6	3334.26
M21	4639.55	0	2	2	2	2	0.00	9279.10	9279.10	9279.10	2	9279.10

M22	2952.16	18	24	8	8	8	53138.88	23617.28	23617.28	70851.84	11	32473.76
M23	1385.09	0	0	0	0	0	0.00	0.00	0.00	0.00	1	1385.09
M24	10231.42	9	2	6	6	6	92082.78	61388.52	61388.52	20462.84	3	30694.26
M25	1529.68	4	0	5	5	5	6118.72	7648.40	7648.40	0.00	6	9178.08
M26	1254.71	3	1	1	1	1	3764.13	1254.71	1254.71	1254.71	2	2509.42
M27	8615.89	6	1	2	2	2	51695.34	17231.78	17231.78	8615.89	1	8615.89
M28	2567.89	0	2	1	1	1	0.00	2567.89	2567.89	5135.78	8	20543.12
M29	15152.17	0	0	2	2	2	0.00	30304.34	30304.34	0.00	1	15152.17
M30	2998.16	3	1	1	1	1	8994.48	2998.16	2998.16	2998.16	3	8994.48
M31	5177.52	12	0	3	3	3	62130.24	15532.56	15532.56	0.00	10	51775.20
M32	1244.32	3	3	3	3	3	3732.96	3732.96	3732.96	3732.96	1	1244.32
M33	2790.42	5	0	3	3	3	13952.10	8371.26	8371.26	0.00	1	2790.42
M34	700.63	4	1	3	3	3	2802.52	2101.89	2101.89	700.63	2	1401.26
M35	4712.30	0	3	0	0	0	0.00	0.00	0.00	14136.90	6	28273.80
M36	225.52	1	0	0.2	0	1	225.52	0.00	225.52	0.00	1	225.52
M37	5089.81	0	1	0.12	0	1	0.00	0.00	5089.81	5089.81	1	5089.81
M38	52.82	26	0	7	7	7	1373.32	369.74	369.74	0.00	1	52.82
M39	7055.76	2	0	1	1	1	14111.52	7055.76	7055.76	0.00	2	14111.52
M40	20318.63	0	1	1	1	1	0.00	20318.63	20318.63	20318.63	2	40637.26
M41	198.00	6	0	2	2	2	1188.00	396.00	396.00	0.00	1	198.00
M42	11323.33	1	1	2	2	2	11323.33	22646.66	22646.66	11323.33	1	11323.33
M43	1478.50	16	13	17	17	17	23656.00	25134.50	25134.50	19220.50	8	11828.00
M44	14513.65	0	9	4	4	4	0.00	58054.60	58054.60	130622.85	5	72568.25
M45	636.22	36	12	23	23	23	22903.92	14633.06	14633.06	7634.64	11	6998.42
M46	2425.52	24	14	17	17	17	58212.48	41233.84	41233.84	33957.28	24	58212.48
M47	736.64	4	0	1	1	1	2946.56	736.64	736.64	0.00	2	1473.28
M48	5675.51	29	1	13	13	13	164589.79	73781.63	73781.63	5675.51	2	11351.02
M49	4459.26	1	8	4	4	4	4459.26	17837.04	17837.04	35674.08	2	8918.52
M50	106.31	161	0	45	45	45	17115.91	4783.95	4783.95	0.00	200	21262.00
M51	2437.72	0	10	0	0	0	0.00	0.00	0.00	24377.20	9	21939.48
Total		433	186	224.07	223	229	691434.66	529286.38	548442.82	565389.92	409	638934.60

Low Demands

Item	NSN Value	Demand	Current Qty	Current Value	AFSAC Forecast	AFSAC Round Dn	AFSAC Round Up	AFSAC Dollars Dn	AFSAC Dollars Up	Actual Dem Dollar value
L35	2148.15	2	3	6444.45	0	0	0	0.00	0.00	4296.30
L34	7597.28	1	1	7597.28	1.6248	2	2	15194.56	15194.56	7597.28
L33	10869.95	1	1	10869.95	0.6864	0	1	0.00	10869.95	10869.95
L32	1293.60	2	14	18110.40	0.2904	0	1	0.00	1293.60	2587.20
L31	1140.76	2	13	14829.88	1.9992	2	2	2281.52	2281.52	2281.52
L30	2559.99	1	3	7679.97	0	0	0	0.00	0.00	2559.99
L29	241.92	1	2	483.84	0.6864	0	1	0.00	241.92	241.92
L28	1956.43	2	1	1956.43	1.8744	2	2	3912.86	3912.86	3912.86
L27	1387.37	1	1	1387.37	0.624	0	1	0.00	1387.37	1387.37
L26	2492.00	1	2	4984.00	0	0	0	0.00	0.00	2492.00
L25	2778.60	1	1	2778.60	0	0	0	0.00	0.00	2778.60
L24	2337.51	2	7	16362.57	5.6232	6	6	14025.06	14025.06	4675.02
L23	1650.00	1	1	1650.00	0	0	0	0.00	0.00	1650.00
L22	6647.65	2	3	19942.95	1.7496	2	2	13295.30	13295.30	13295.30
L21	20620.40	2	1	20620.40	0	0	0	0.00	0.00	41240.80
L20	964.21	1	1	964.21	0.2904	0	1	0.00	964.21	964.21
L19	6759.50	1	2	13519.00	0	0	0	0.00	0.00	6759.50
L18	8117.53	2	1	8117.53	0.3312	0	1	0.00	8117.53	16235.06
L17	1828.48	1	1	1828.48	0.7488	0	1	0.00	1828.48	1828.48
L16	51.21	1	100	5121.00	1.968	2	2	102.42	102.42	51.21
L15	15700.00	1	5	78500.00	0	0	0	0.00	0.00	15700.00
L14	3375.20	2	2	6750.40	3.7488	4	4	13500.80	13500.80	6750.40
L13	1034.82	2	1	1034.82	0	0	0	0.00	0.00	2069.64
L12	2176.28	1	2	4352.56	0	0	0	0.00	0.00	2176.28
L11	206.89	1	2	413.78	0.5832	0	1	0.00	206.89	206.89
L10	273.04	1	1	273.04	5.2488	5	5	1365.20	1365.20	273.04
L9	850.30	2	1	850.30	0.3312	0	1	0.00	850.30	1700.60
L8	1650.00	1	2	3300.00	0	0	0	0.00	0.00	1650.00
L7	730.79	1	2	1461.58	0	0	0	0.00	0.00	730.79
L6	555.17	1	4	2220.68	2.2488	2	2	1110.34	1110.34	555.17
L5	1186.62	1	2	2373.24	0	0	0	0.00	0.00	1186.62
L4	16920.22	1	6	101521.32	1.3728	1	1	16920.22	16920.22	16920.22
L3	3220.60	2	1	3220.60	0.3744	0	1	0.00	3220.60	6441.20
L2	637.36	1	1	637.36	0	0	0	0.00	0.00	637.36
L1	10342.53	2	1	10342.53	0	0	0	0.00	0.00	20685.06
Total		48	192	382500.52	32.4048	28	38	81708.28	110689.13	205387.84

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13. ABSTRACT (Maximum 200 words) The United States (US) promotes collective security in the Free World via the Foreign Military Sales (FMS) program. FMS customers prefer to acquire weapon system logistic support through FMS rather than by direct commercial vendor support. Ninety-seven percent of the follow-on logistics requirements are submitted via a special program called Cooperative Logistics Supply Support Arrangement (CLSSA). CLSSA, while sound in theory, has been a poor performer. The USAF must modify the CLSSA program or risk losing future FMS to competing nations. Modifying CLSSA to utilize an automated forecasting process will greatly improve customer service. Efficient and timely logistic support is a key decision factor as friendly nations evaluate the source of their next major weapon system acquisition. The US as a whole will gain from the USAF's new approach to CLSSA through the political, military and economic benefits that result from increase FMS demand for US weapon systems. This study measured the relative accuracy of four time series forecasting methods in predicting future demands for CLSSA Investment Items. The double exponential smoothing, adaptive response, and classical decomposition were compared to the AFSAC retention model to determine the impact of changing to an automated method. The results favored the implementation of the AFSAC retention method with some minor modifications in the weighting scheme, rounding rules, and demand smoothing.

14. SUBJECT TERMS
Forecasting, Reparable Items, Inventory Management, Retention, Cooperative Logistics Supply Support Arrangement (CLSSA), Foreign Military Sales (FMS)

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